

RESEARCH ARTICLE

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Facilitating higher photovoltaic penetration in residential distribution networks using demand side management and active voltage control

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Funding information

Engineering and Physical Sciences Research Council, Grant/Award Number: EP/H040331/1

Abstract

Future power networks are certain to have high penetrations of renewable distributed generation such as photovoltaics (PV). At times of high PV generation and low customer demand (e.g., summer), network voltage is likely to rise beyond limits mandated by grid codes resulting in a curtailment of PV generation, unless appropriate control means are used. This leads to a reduction in energy yield and consequently reduces the economic viability of PV systems. This work focuses on scenario-based impact assessments underpinned by a net prosumer load forecasting framework as part of power system planning to aid sustainable energy policymaking. Based on use-case scenarios, the efficacy of smart grid solutions demand side management (DSM) and Active Voltage Control in maximizing PV energy yield and therefore revenue returns for prosumers and avoided costs for distribution networks between a developed country (the UK) and developing country (India) is analyzed. The results showed that while DSM could be a preferred means because of its potential for deployment via holistic demand response schemes for India and similar developing nations, technically the combination of the weaker low voltage network with significantly higher solar resource meant that it is not effective in preventing PV energy curtailment.

KEYWORDS

active voltage control, demand side management, distributed generation, energy yield curtailment

1 | INTRODUCTION

The decarbonisation of the energy network has created higher demand for electricity over oil and coal. Some of the electrical power network assets such as transformers and switchgear assets were installed as early as the 1950s and are still in use today.¹ For example, the UK's National Infrastructure Delivery Plan 2016–2021 identifies that “much of the existing infrastructure which has served us well is now old” and that “major investment is required to accommodate new generation and replace aging assets”. However, there is also a greater focus now on lowering the cost of delivering

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electricity. The performance-based electricity distribution model Revenue = Incentives + Innovation + Outputs model of the UK which has been in operation from 2015² is representative of this drive. In the continuing drive to reduce cost, given the high cost of assets, especially at the transmission and sub-transmission voltage levels, it is safe to assume that even in the near- or medium-term, power networks will be mostly composed of present-day assets.

There will be high volumes of customer-side renewable generation due to the decarbonisation targets. However, the exact penetration levels, renewable generation type and their share in the demand mix are presently uncertain. Due to technological advances, photovoltaics (PV) system costs have been on a continuous decline and, by 2017, PV module was more than 80% cheaper compared to a decade ago.³ PV systems also have a low maintenance cost due to their static nature. At the domestic residence level, PV systems is one of the most popular types of renewable generation. Currently, Germany has the highest PV installed capacity in Europe; with over 49 GW.⁴ More than 98% of PV systems are connected to low voltage (LV) distribution networks.⁵ Even though the present levels of PV penetration in most other countries are relatively low, given the ambitious targets (e.g., 175 GW by 2022 for India by the Ministry of New & Renewable Energy), scenarios similar to Germany with high PV penetration is not far away.

A decentralized power supply becomes problematic for the traditional operating mode of the electricity network where net load on the network is largely foreseeable, power supply is controlled and there is a uni-directional electricity flow from large generators to consumers.⁶ Conventional power distribution networks have limited PV generation hosting capacity and 'high PV generation – low demand' conditions can result in network voltage limit violations.⁷ Extensive research has recently been carried out on assessments of the impacts of distributed generation on the electricity distribution network.^{8–10} Such impact analyses have been able to identify the detrimental effect of future load on network assets.^{11–13} Accelerated aging of transformer oil and insulation,¹¹ deterioration of functioning of aged circuit breakers and switchgear,¹² and higher maintenance requirements of transformer tap changers¹³ are a few of the identified detrimental effects that have a direct commercial significance.

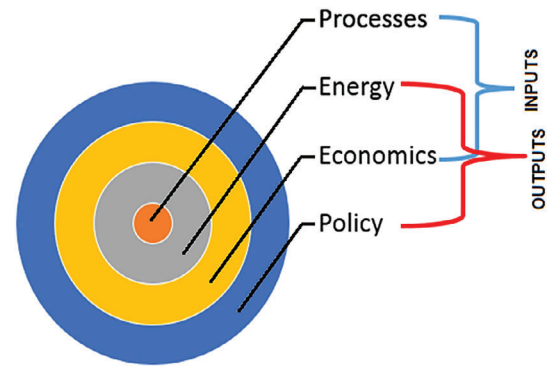
While there are schemes in place for prioritizing the grid injection of renewable energy,¹⁴ the detrimental effects identified as associated with increase in PV penetration levels have resulted in grid codes making active curtailment of PV generation becoming a mandatory requirement now in several countries.¹⁵ For example, according to Engineering Recommendation G98, PV systems in the UK LV distribution networks are required to curtail generation when the voltage rise at the point of connection exceeds the mandated limit.¹⁶

Incentives like feed-in tariffs offered by government bodies have driven the installation of PV systems, but, as customers have to invest a large capital on installing PV systems and are getting paid for the energy they generate. Curtailing PV generation reduces the PV energy yield and therefore the systems financial viability. Maximizing the energy yield and penetration levels of PV systems is therefore important with respect to both climate change mitigation and energy economics.

Several approaches have been considered in the literature in order to improve the network hosting capacity of PV and other renewables and maximize the energy capture. These approaches include network reinforcement, network reconfiguration, static VAR control, energy storage,¹⁷ and smart grid solutions such as Demand Side Management (DSM)¹⁸ and Active Voltage Control (AVC).^{15,19}

Power networks are currently moving into the smart grids paradigm. The inherent cost attached to smart grids technologies means that the global economic inequality will be reflected in their deployment. Developing nations with lower economic reserves to spare are often constrained in terms of the level and nature of changes they could make to their power networks. However, owing to energy supply deficits, load growth, dependency on fossil fuel imports, and so forth, developing nations are in greater need of cheaper low carbon generation. This can only be realized through efficient and sustainable energy policies. Figure 1 is representative of the modeling requirements within the energy policy nexus. A multitude of scenarios of with variations in underlying technical processes, energy behavior and associated economics needs investigation for effective policymaking.

As energy flow becomes inevitably more complex with larger integration of renewable generation, electric vehicles and energy storage in modern power networks, power system planning methods are becoming more complicated compared to how they were with conventional, mostly thermal, generation. It was evident from a survey of recent literature on power system planning that there is a significant focus recently on large-scale renewable integration, specifically with regards to generation expansion planning focusing on national energy policies.²⁰ Majority of literature tends to concentrate on optimization of transmission and distribution planning, ultimately underpinned by load flow analysis.²¹ As an emerging area there is a high level of attention given to energy storage from the point of view of technical constraints, given the uncertainty around their economics.²² There is also focus on the drivers and challenges of renewable penetration such as

FIGURE 1 Outline of modeling requirements for energy policymaking

carbon tax²³ and resource uncertainty and variability.²⁴ Resource planning²⁵ and mitigating strategies such as DSM and OLTC for voltage rise mitigation²⁴ is investigated in this context.

Authors of Reference 26 reviewed power system planning challenges for India with increasing penetration of renewables given the ambitious installed capacity targets. The current energy policies are summarized, and it is recommended that India learn from international experiences and adopt best practices from developed countries. The need for DSM and advanced forecasting methods is also emphasized along with other recommend actions to facilitate higher renewable penetration. In Reference 27, a method combining probabilistic duck curve and probabilistic ramp curve to efficiently compensate the imbalance between the high PV generation time and peak time of load was demonstrated for a use case of China. Reference 28 emphasizes that load forecasting is often the first step in power system planning. Plug-in electric vehicles (PEVs) and the Korean government PEV targets are focused on. A stochastic method for forecasting PEV load profiles is introduced focusing on the PEV expansion target, statistics of existing vehicles and consumer numbered connected to substations. Reference 29 focuses on the voltage rise problem with increased renewable penetration for aging power networks and introduces an algorithm for carrying out decision-making on asset upgrades or network reinforcement by addition of components and modification of topology. The trade-off between power line upgrades and placements and operation of on-load tap changing (OLTC) transformers in the network was investigated from the point of view of technical constraints.

In Reference 30, authors identify that increasing renewable penetration is confidential with increasing need for flexibility within power systems. Market design is identified as the structural tool that can facilitate flexibility. Potential market reforms are outlined with a focus on DSM. The impact of the difference in nature and requirements of different regional networks and availability of flexible loads are acknowledged. It is recommended that future research focus on planning and operation of power system factoring the difference into account. In Reference 31, a multi-region power system planning approach named REPLAN is proposed for Nigeria. The focus was on improved energy exporting and importing arrangement between regions and overall energy cost reduction by forecasting inter-regional transmission capacity and pathways for developing regional generation. Although the study emphasized the need to investigate local (regional) network models, it was aimed at long-term power system planning and not on diurnal power system operation.

It was evident from the literature surveyed that there is a strong focus on energy policies. However, the focus is mostly at the higher-level vision-type policies, often at the national level, setting the energy targets rather than the policies or grid codes at the operational level, which translate the envisioned benefits to reality. Revenue from energy is the basis of renewable energy economics. Policy makers will not be to capture the full picture for facilitating higher penetration of renewable like PV based on research that just focus on maximum hosting capacity, the implications of technical measures/constraints to PV energy and PV system owners also need to be understood. In this context, the main aim and contribution of this work is to support power system planning by means of scenario-based impact assessments and thus aid sustainable energy policymaking, especially for developing countries. The efficacy of smart grid solutions (DSM and AVC), between developed and developing countries, in facilitating higher PV penetration in residential distribution networks, given grid code requirements, is analyzed. Select use case scenarios of the UK and India are used as examples of a developed and a developing country. A net prosumer load forecasting framework is introduced, and its application is demonstrated for the use cases.

The remainder of the article is organized as follows: In Section 2, the research methods along with case studies and simulation details are discussed, with the case study network description for Newcastle (UK) and Mumbai (India) in Section 2.1, the description of parameters for PV simulation in Section 2.2 and the proposed smart grid solutions in

Section 2.3. Section 3 describes the methodology used for assessing the performance of the chosen smart grid solutions: demand-side management and AVC. Section 3.1 explains the net load profile generation for both Newcastle and Mumbai, while PV energy yield estimation algorithms are described in Section 3.2. Simulation results are discussed in Section 4, which is classified into three scenarios: (i) base case in Section 4.1, (ii) the case with DSM and (iii) case with DSM and AVC. And finally, conclusions are drawn in Section 5.

2 | METHODS

2.1 | Distribution networks considered

In this paper, we consider two LV distribution network examples: One from the UK (as an example of a developed country) and one from India (as an example of a developing country). For the UK, Newcastle upon Tyne was chosen as the location for investigation. A typical UK distribution network model shown in Figure 2 from Reference 32 was used. The LV feeder shown in detail from the secondary distribution transformer has 384 houses. The total number of houses connected to an 11 kV feeder is 3072 ($= 8 \times 384$) and to the 33/11 kV substation is 18,432 ($= 6 \times 3072$) houses. For India, Mumbai was chosen as the location for investigation. The distribution network model shown in Figure 3 was used. The model consists of a 33/11 kV 15 MVA transformer substation with nine outgoing feeders (11 kV), supplying 14,385 houses. A typical 415 V LV feeder (shown in red) supplying 385 houses was considered in detail, similar to Newcastle.

2.2 | PV generation simulation

A 3.6 kW polycrystalline rooftop residential grid-connected PV system was considered as typical for both countries. PVGIS (Photovoltaic Geographic Information System)³³ was used as the solar resource database as well as PV generation simulation tool. Technical data of Sharp ND-R250A5 polycrystalline PV modules and SMA H5 inverter were used for simulation.

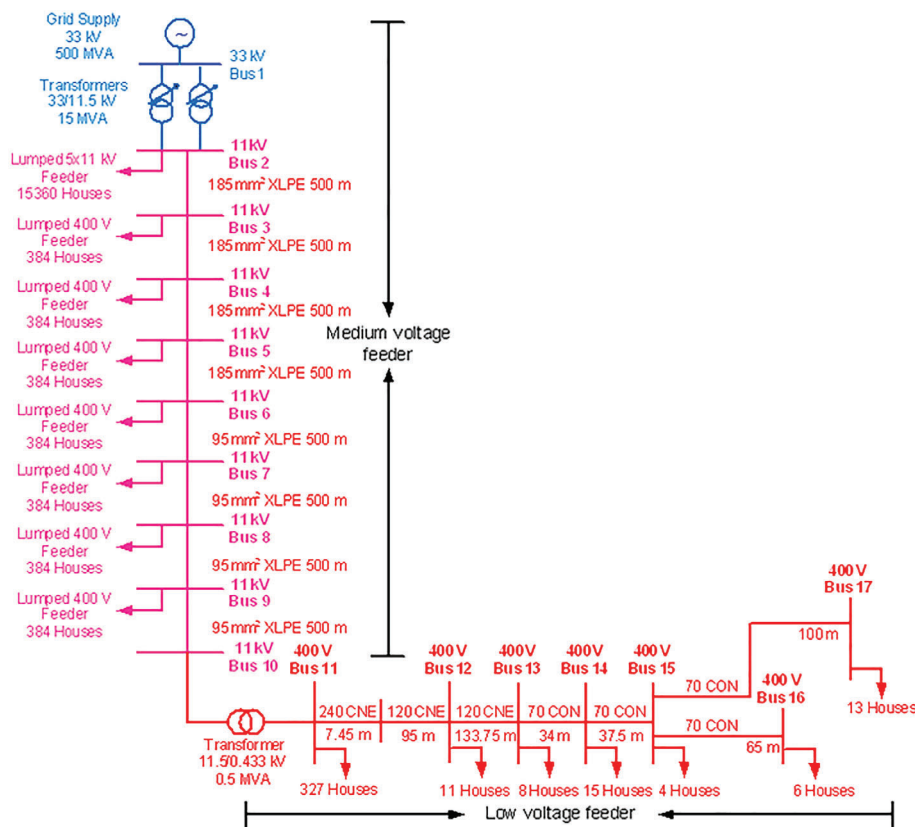
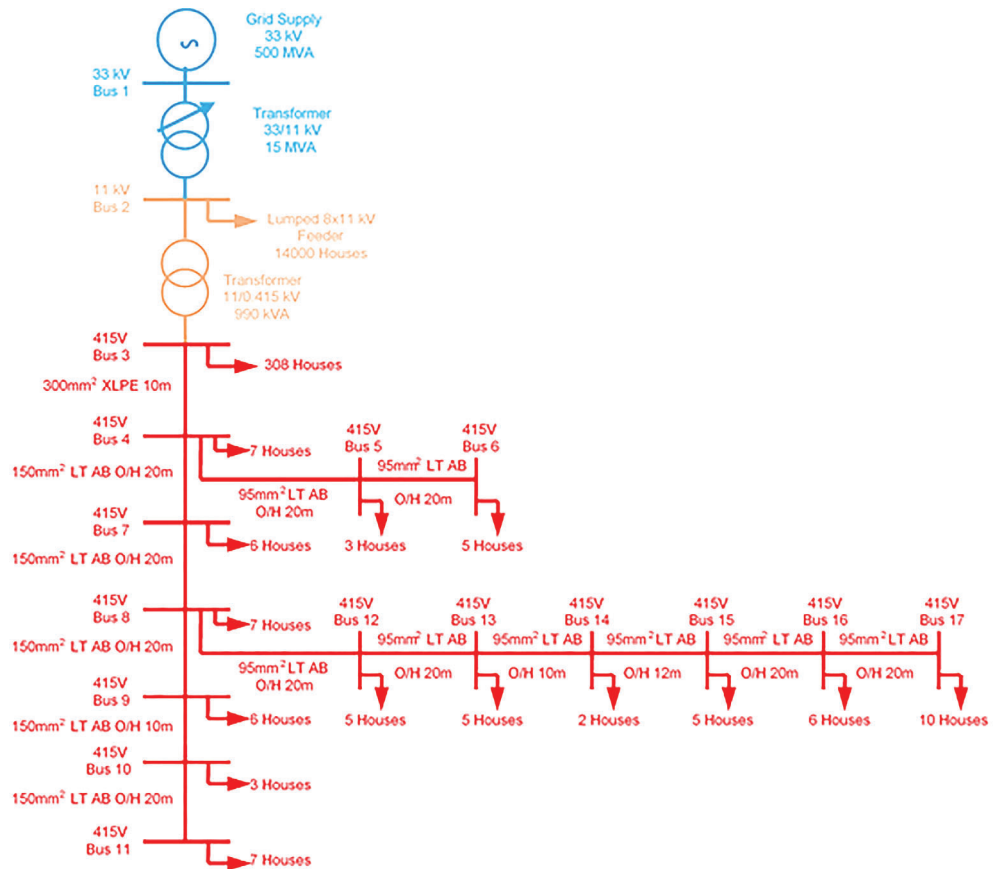


FIGURE 2 Typical distribution network of UK³²

FIGURE 3 Typical distribution network in India



Daily PV generation profiles for a typical year were generated for both locations. Systems were assumed to be stationary and at optimal tilt. The PV system's annual energy yield was found to be 3280 kWh (equivalent to 911 kWh/kW) for Newcastle. For the system in Mumbai, the yield was around 80% more than that of Newcastle at 6017 kWh (equivalent to 1671 kWh/kW).

2.2.1 | PV penetration scenarios for assessment

In this study, PV penetration level was defined as the fraction of the number of houses in the distribution network considered having a typical PV system. Eleven scenarios each, are studied for both Newcastle and Mumbai cases. PV penetration level is varied from 0% to 100% in steps of 10%, to create the 11 scenarios.

2.3 | Smart grid solutions considered

2.3.1 | Demand side management

DSM is the control of customer loads in order to achieve a better match between the available supply and the demand. Of the DSM strategies available, the load shifting strategy (Figure 4), which is the movement of operation of selected loads between times of the day, is chosen in this work. This strategy is most suited for maximizing self-consumption of energy (and hence the economic value) from PV systems installed at customer premises. DSM can be either 'Active' or 'Passive'. 'Active' Demand Side Management (ADSM) is defined as the automated (intelligent) control of residential electricity demand to meet the needs of the power supply system.³⁴ This has become possible with the roll out of smart meters and the development of home automation technologies. 'Passive' DSM (PDSM) requires customers to be active participants, the control action of load shifting is realized by the customers based on inputs from network operator/electricity company. DSM implementations can be based on price signals such as time of use (ToU) tariffs and real-time pricing or based on

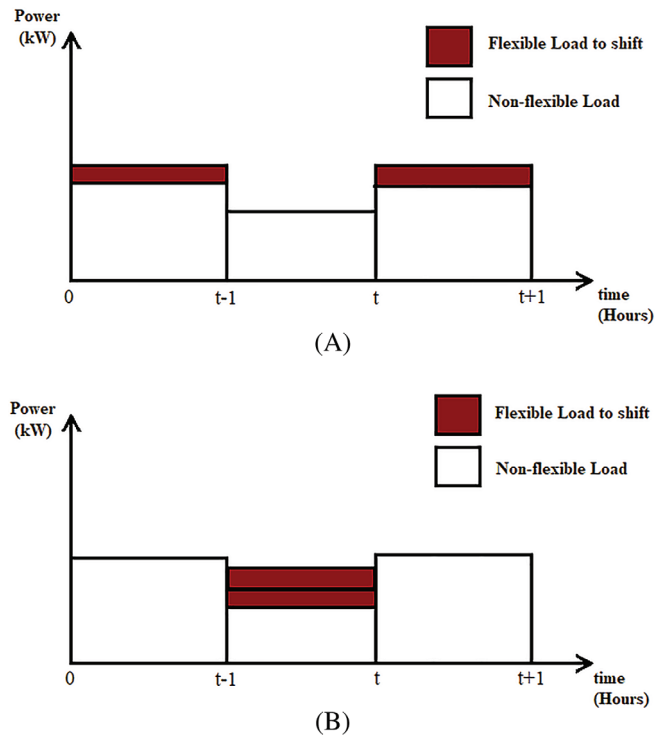


FIGURE 4 (A) Before load shifting and (B) After Load Scheduling

incentive schemes, for example, buy-back programs.³⁵ Figure 5 is representative of a plausible ADSM scheme and shows an ADSM controller incorporated into a smart grid architecture³⁶ in which maximization of PV energy capture would be realized through direct load control by the ADSM controller. In PDSM a similar maximization of PV energy could be realized, for example, through a mobile phone app that evokes customer load action.³⁷

Load shifting can be expressed mathematical as^{38,39}:

$$\text{Load Shifting} \rightarrow \text{Minimize} \sum_{t=1}^N (P_{\text{load}}(t) - (\text{Objective}(t)))^2$$

$$\text{Desired Consumption at time "t"} \rightarrow \text{Objective}(t)$$

$$\text{Actual Consumption at time "t"} \rightarrow P_{\text{load}}(t) = \text{Forecast}(t) + \text{Connect}(t) - \text{Disconnect}(t) \quad (1)$$

where,

$\text{Forecast}(t) = \text{Forecasted consumption at time } t$

$\text{Connect}(t) = \text{Connected load amount at time } t$

$\text{Disconnect}(t) = \text{Disconnected load amount at time } t$

Appliances chosen as flexible loads for DSM in this study is shown in Table 1. The table also shows the household share (percentage of household with the specific appliance), cycle duration and energy consumption/cycle considered for the chosen flexible loads based on information assimilated from References 40-42. While the share of Dishwashers was below 1% in India before 2020, manufacturers have witnessed a 400% surge in demand due to COVID lockdown and homeworking restrictions.⁴³ Mumbai, being the commercial capital of India, it is assumed that the increase in PV penetration will be coincidental with an increase in uptake of Dishwashers.

Load profiles of these flexible loads chosen for DSM for a typical day were available from Reference 44 for the UK. Owing to the lack of such appliance level consumption data in India, the same profiles were assumed for India. Figure 6 shows the load profiles for the three categories of flexible loads.

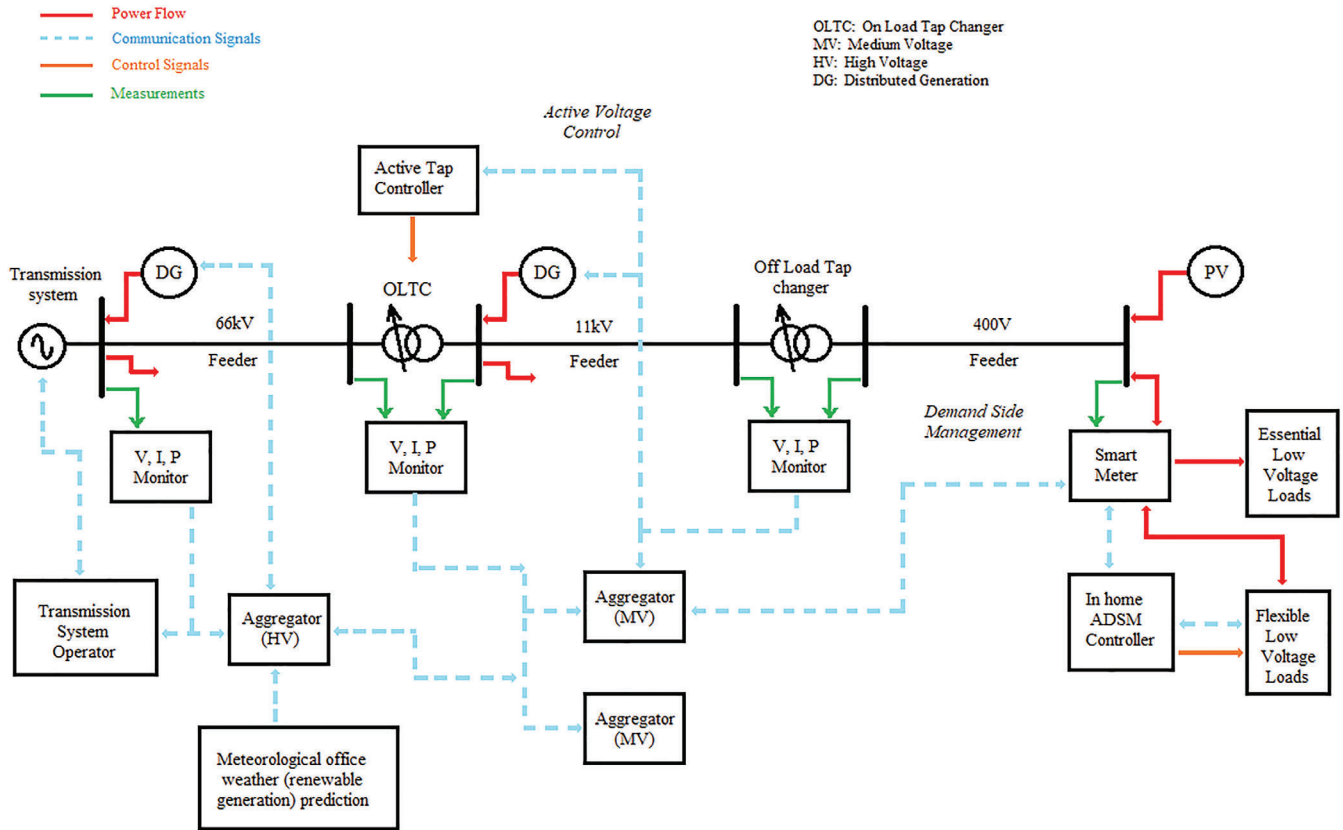


FIGURE 5 Smart grid architecture (Source: adapted from Reference 34) with an indicative ADSM controller

TABLE 1 Details of flexible loads chosen for DSM

Appliance	Household share in the UK (%)	Household share in India (%)	Energy consumption/cycle (kWh)
Washing machine	95	43	1.8
Dishwasher	40	Below 1%	1.2
Electric water heating	10	45	3.0

With the use of appropriate control logic and knowledge of the network topology, the feeder level controller (Aggregator MV) shown in Figure 5 would be able to make nodal voltage predictions. The in-home ADSM controller can receive these predictions via the smart meter and trigger load-shifting of the flexible loads according to the DSM program.

2.3.2 | Active voltage control

AVC is a part of the active management of the network. Grid codes usually require that the voltage at the end customer terminal does not deviate from the nominal value by more than a few percent (e.g., within -6% to $+10\%$ for the LV network in Europe). To satisfy this requirement, the voltage of all nodes in the network should be kept close to their nominal value at the extremities of the distribution network operation. Transformer tap changers, voltage regulating transformers and reactive power compensation are some of the techniques that are used for achieving this control.⁴⁵ Amongst these, transformer tap changers are the most common and hence, in this study, AVC is considered by means of transformer tap changing, as shown in Figure 7 for one phase of a three-phase primary substation transformer. The OLTC on the high voltage winding (winding 2) regulates the voltage by varying the transformer ratio V_2/V_1 . Tap position 0 corresponds to no voltage correction and tap position N_{Taps} yields the maximum voltage correction.

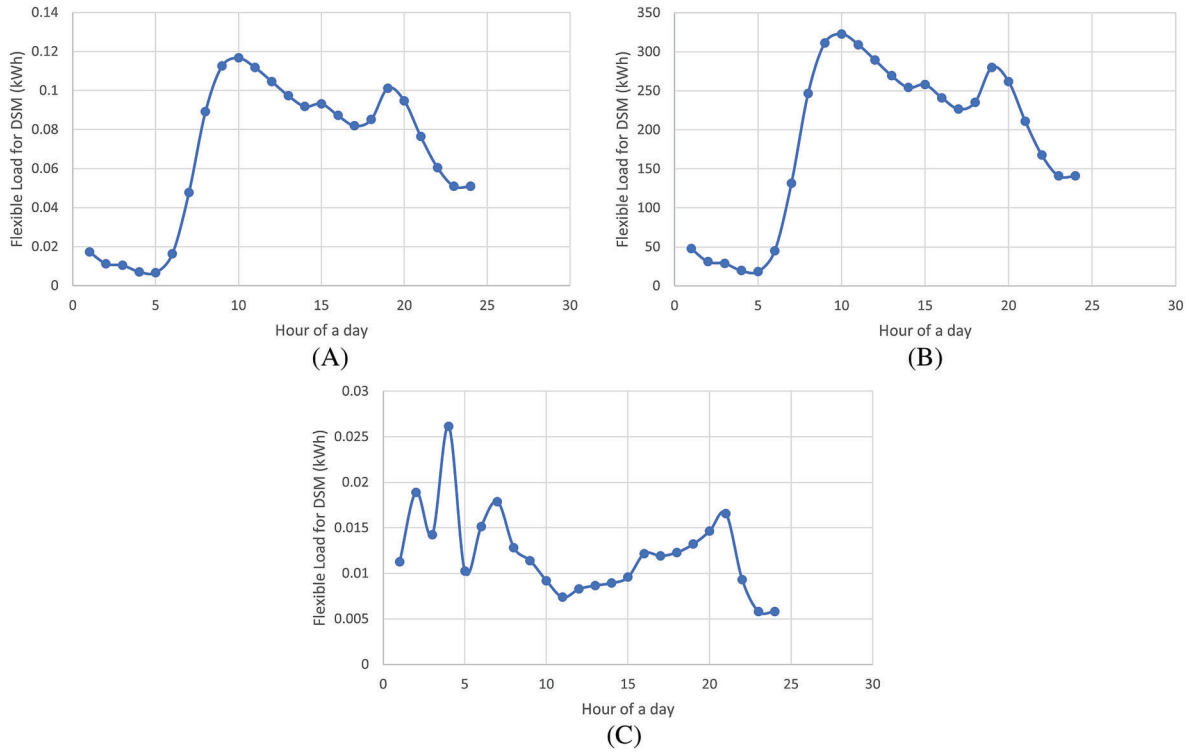


FIGURE 6 Typical load profiles of flexible loads (A) washing machine, (B) dishwasher, and (C) electric water heating for a single domestic dwelling

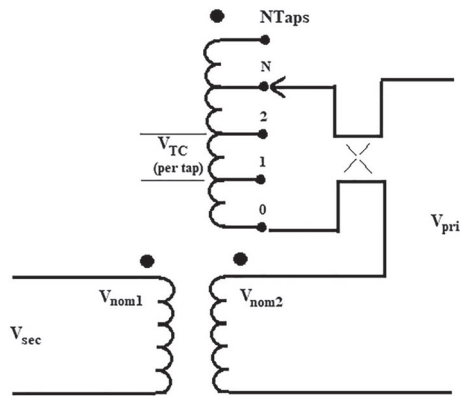


FIGURE 7 One phase of primary substation transformer

OLTC on winding 2

Reversing the switch connects the regulation winding in opposite polarity and yields negative tap positions. Hence the tap range is $-N_{Taps} \leq N \leq +N_{Taps}$. Voltage regulation by the OLTC can be described by the equation

$$V_{sec} = \frac{V_{pri}}{(1 + N \cdot V_{TC})} \frac{V_{nom1}}{V_{nom2}} \quad (2)$$

where V_{nom1} and V_{nom2} are the nominal voltages of winding 1 and 2, N is the tap position, V_{sec} is the transformer output voltage after tap changing, V_{pri} is the source voltage incoming to the transformer primary part and V_{TC} is the voltage per tap.

Normally, control of OLTCs at primary substations is by means of an automatic voltage controller, which controls the tap changer on the high voltage side of the transformer, in order to keep the voltage on the LV side within limits. In contrast to conventional voltage regulation (which uses Scalar LDC), the automatic voltage controllers in this case deploys Vector Line Drop Compensation (LDC), which is intended to keep the voltage in the distribution feeder within limits by compensating for voltage drop along fictitious impedance and modifying the controller algorithm to keep the

transformer terminal voltage equal to a reference value. As vector LDC also counts on changes in power factor, the results are more reliable and the mathematical expression is as follows,⁴⁶

$$\text{Reference Voltage} \rightarrow V_{ref}(t) = |V_{sec}(t) - \sqrt{3}I(t).(R_{ref} + jX_{ref})| \quad (3)$$

where

$$V_{sec}(t) = \text{Secondary Voltage of Transformer}$$

$$R_{ref} = \text{Line Resistance}$$

$$X_{ref} = \text{Line Reactance}$$

$$I(t) = \text{Line Current}$$

Tap-changer is operated by comparing the reference voltage with the deadband which is a small voltage range introduced in the transformer's design in order to avoid unnecessary switching around the target voltage.

Tap movements are usually made if $|V_m - V_{ref}| > \text{Deadband}/2$ for a certain time delay of t_{step} (which is 1-min duration in this study) according to the following equation:

$$\text{Tap}_{change}(t + t_{step}) = \begin{cases} -1, & \text{if } V_{max}(t) > V_{up}^{TC}, V_{min}(t) - V_{TC} \geq V_{low}^{TC} \\ 1, & \text{if } V_{min}(t) < V_{up}^{TC}, V_{max}(t) + V_{TC} \leq V_{low}^{TC} \\ 0, & \text{else} \end{cases} \quad (4)$$

where

$$V_{max} = 1.1\text{pu} - \text{Voltage at current tap position}$$

$$V_{min} = \text{Voltage at current tap position} - 0.9\text{pu}$$

$$V_{TC} = \text{voltage per tap} = 0.125\text{pu}$$

$$V_{low}^{TC} = \text{minimum deadband voltage} = -2.5\% \text{ of } V_{TC}$$

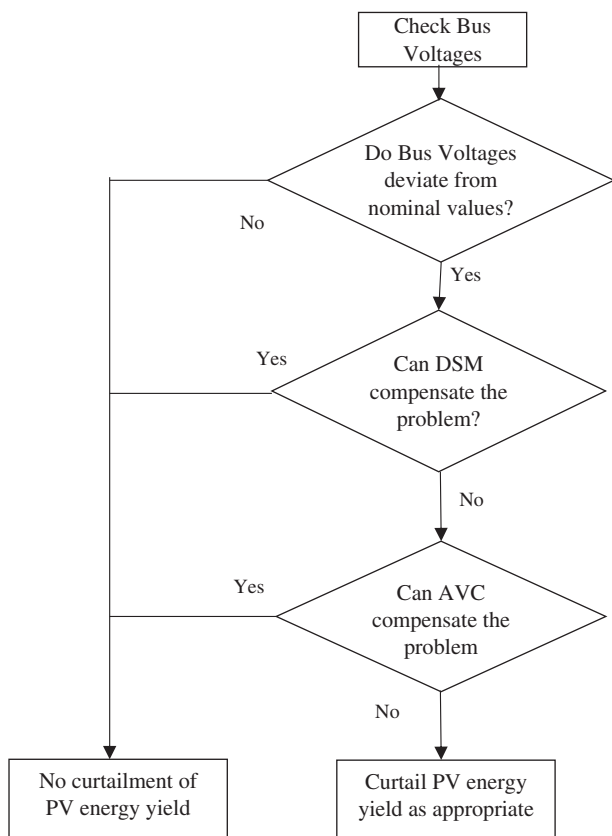
$$V_{up}^{TC} = \text{maximum deadband voltage} = +2.5\% \text{ of } V_{TC}$$

3 | PERFORMANCE ASSESSMENT

High PV penetration levels can result in situations where the LV network voltage exceeds the statutory limits. Current grid codes (for example, G98 in the UK) require residential PV systems to turn-off and curtail generation during periods of voltage rise. The main aim of this paper is to analyze the efficacy of smart grid solutions (DSM and AVC), between developed and developing countries, in facilitating higher PV penetration in residential distribution networks, given grid code requirements using the 11 PV penetration scenarios for Newcastle and Mumbai described in the previous sections. LV distribution networks of both the UK and India were designed for an After Diversity Maximum Demand (ADMD) of 2 kW per customer. However, in terms of PV, Mumbai's output is much higher compared to Newcastle for the same PV system size. As described in Section 2.3.1 it is possible to realize a certain ADSM load action also through PDSM. PDSM as a holistic strategy without the need for smart appliances or direct load control would be preferable in the first instance for developing countries like India because of economic reasons. As such, DSM is chosen as the first preferred solution to prevent PV curtailment, followed by AVC. The two-stage approach is shown in Figure 8. The objective is to maximize the PV energy capture by self-consumption and consequently to reduce the burden caused by the reverse power flow on electrical network assets to maintain the optimal assets' lives.

For load shifting, the scenario-based assessments considered a representative DSM logic outlined in Figure 9 is applied to each flexible load category (washing machine, dishwasher, and electric water heater). Figure 10 outlines the AVC operation scheme considered for the study.

FIGURE 8 Maximizing PV energy capture by DSM and AVC

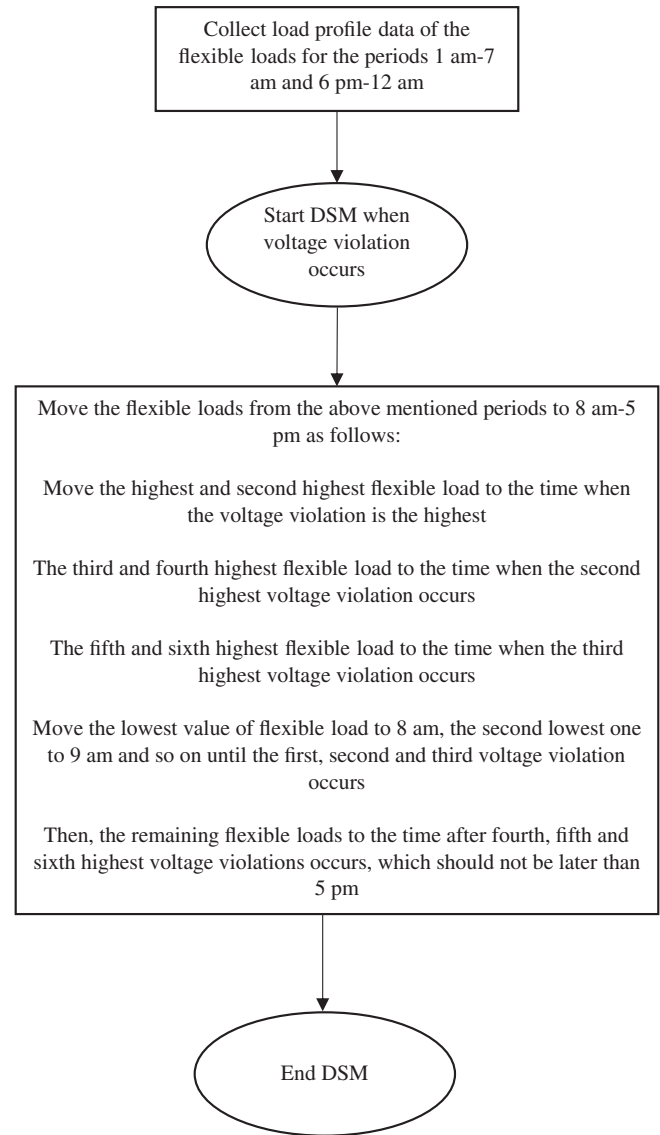


3.1 | Net load profiles

Residential load profiles represent the variation of After Diversity Maximum Demand (ADMD) of domestic consumers over a day. The standard method of constructing an hourly load profile is by recording the energy consumption, at feeder or substation level in an electricity distribution network, at regular intervals and dividing this by the number of customers on that feeder to produce the ADMD. The nature of customers is changing under de-carbonization. Residential customers with generating technologies such as PV are prosumers as they produce and export electricity in addition to the typical consumer roles. In the smart grid context, historic forecasts of load profile will not be appropriate. Net load profiles at the residential customer level will need to be prosumption profiles, factoring in the drastic changes in load (for example, due to electric vehicles [EV], heat pumps, and so forth) and at-home generation technologies (PV, Micro-CHP, and so forth). Synthetically generated net load profiles are therefore important for scenario-based assessment studies.

Several studies have used artificial intelligence models for predicting energy demand of buildings.⁴⁷ Günay⁴⁸ modeled the gross electricity demand in Turkey using Artificial Neural Network (ANN) models with weather and socio-economic factors as inputs. Zameer et al.⁴⁹ used genetic programming based on an ensemble of neural networks to demonstrate the feasibility of wind energy prediction (in Europe) by using publicly available weather and energy data. With regard to the challenge of predictive modeling for uncertain penetration levels of future distributed resources, a number of researchers have recently had reasonable success by employing statistical probability distributions.^{50–52} For example, Munkhammar et al.⁵² demonstrated the use of the Bernoulli distribution for incorporating EV demand into load profiles. However, these statistical probability distributions fail to take into account the time varying behavior in the energy consumption of distributed resources as they assume a constant load. Therefore, a framework for synthetic net residential load profile generation proposed combining artificial intelligence and statistical probability distributions, that can be used for scenario-based assessment studies, is proposed as shown in Figure 11. The framework summarizes authors' accumulated experience in using artificial intelligence methods and observations of literature.

The net residential load profile generation problem is inherently data centric. The choice of data, artificial intelligence methods, and inclusion of operational elements of the framework such as statistical probability distribution is dictated by the data available. A method tailored for the data available and scenario under consideration, can be generated based on the framework. ANNs are capable of mapping nonlinear relationships between inputs and outputs with

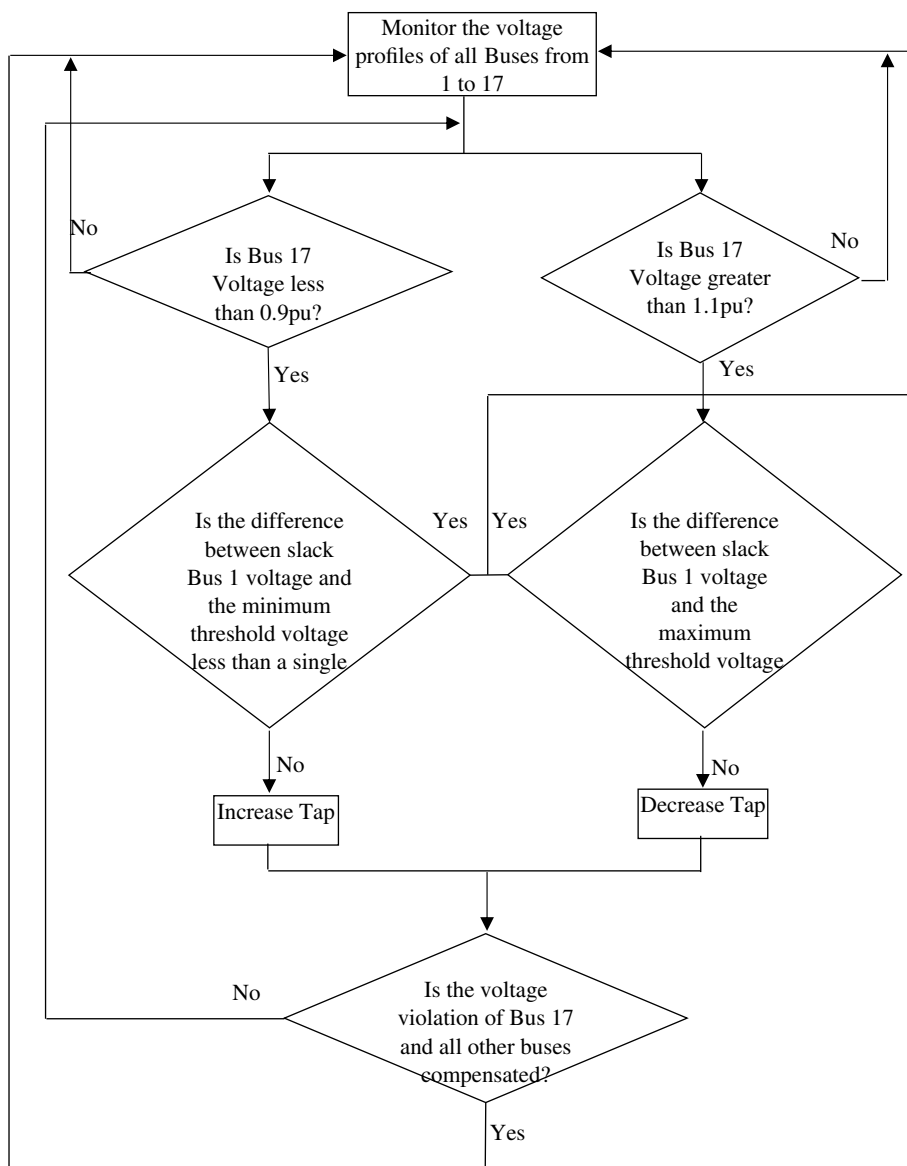
FIGURE 9 The load shifting DSM scheme considered

a high level of accuracy.⁵³⁻⁵⁵ ANNs are used in a wide variety of tasks in different fields including finance, industry, science, and engineering.^{53,56-58} ANNs is particularly suited for load forecasting where high levels of accuracy are required.⁵⁷ ANN based methods were developed for Newcastle and Mumbai and net load profiles were generated for all 11 scenarios described in Section 2.2.1.

3.1.1 | Newcastle case

The authors had previously developed an ANN model in Reference 59 for generating net load profiles for UK residential customers under variable PV generation and electric vehicles (EV) charging penetration scenarios. The model was generated using the Matlab Neural Network Toolbox and was trained using publicly available data. During validation with data that the ANN model had no apriori knowledge of, the model synthetically generated composite load profiles with a combined Mean Absolute Percentage Error (MAPE) of 0.01365 and a root mean square error (RMSE) of 7.81 over a full range of PV and EV penetration scenarios from 0% to 100%. For the Newcastle case study, an improvement in the ANN model performance was focused on. ANN architecture is highly problem dependent⁶⁰ where the choice of number of hidden neurons, hidden layers, and training algorithm are all considered to be critical decisions in improving the performance of an ANN model.^{57,61} Therefore, testing was conducted to find the optimal design network by comparing the performance of 3520 networks created with different combinations of the 17 supervised training algorithms available in

FIGURE 10 AVC operation scheme considered



the Matlab environment, hidden layers from 1 to 6 and nodes in each layer from 1 to 20. The optimal network was found to have 13 neurons in one hidden layer which was trained using the Bayesian regularization backpropagation algorithm. Validation of this model using the same data used with the original model saw the MAPE lower to 0.00608 and the RMSE lower to 3.48.

Figure 12 summarizes the training of the ANN model and its inputs for predicting net load profiles. UKERC⁶² was the source of load data during training. PV generation data was based on PVsyst software simulations using public domain weather data from PVGIS. The net load profiles for different PV penetration scenarios studied in this work for Newcastle were created using five inputs, namely time of day (hour), PV penetration level (0% to 100% in steps of 10%), EV penetration level (set to 0), temperature, and irradiance values. Temperature and irradiance values were from the SARA solar radiation database accessible through the PVGIS website.

3.1.2 | Mumbai case

The ANN model developed and validated by the authors in Reference 63 was used to generate load profiles for Mumbai. Like many developing countries, owing to the lack of resources, there is a severe shortage of data in the public domain. In contrast to the PV data (resolution of 15 min for all days of a typical year), the load data set was extremely limited [48

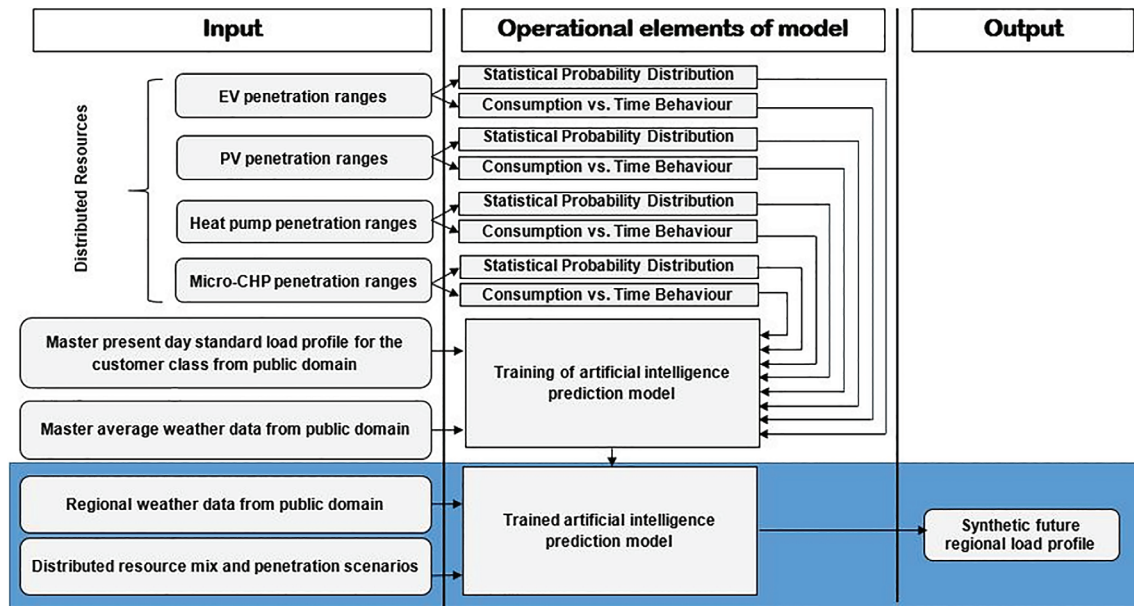
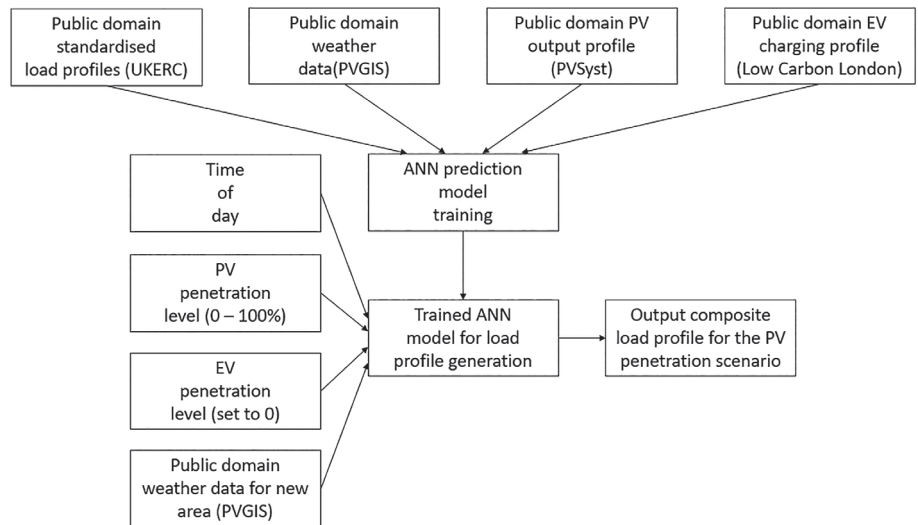


FIGURE 11 Proposed net residential load profile generation framework

FIGURE 12 ANN-based net load profile generation for Newcastle



data values in total, 24 hourly values each for summer and winter]. This made ANN training extremely challenging and was mitigated by means of Bayesian Regularization.⁶³ Figure 13 shows the synthetic residential load profiles for Mumbai generated by the ANN model. However, optimizing the ANN model for extremely limited data posed a challenge, the ANN model could only learn the load behavior not the PV behavior. For this reason, net load profiles were based on summation of ANN predicted load profiles and PVGIS PV generation profiles.

3.2 | PV energy yield estimation algorithms

At the LV distribution level (230/400 V UK, 240/415 V India), the grid codes of both the UK⁶⁴ and India^{65,66} mandate an upper voltage limit of 1.1 p.u. For PV inverters connected to LV networks, G83, the UK's previous grid code required disconnection at the same voltage of 1.1 p.u. However, the new grid code G98 requires PV inverters to disconnect only at 1.14 p.u. It is understood that this is for reasons of stability as disconnection of large amount of renewable generation at

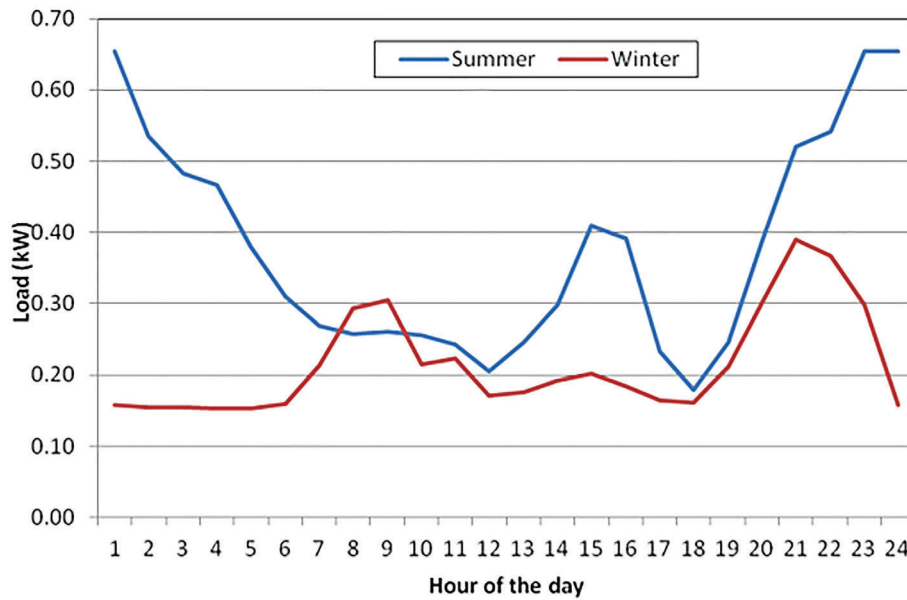


FIGURE 13 ANN generated synthetic residential load profiles for Mumbai

the same instant can create instability. Therefore, there are two voltages which are of significance 1.1 p.u. and 1.14 p.u. Most PV inverters are now manufactured to comply with G98. India also uses the same inverter technologies as the UK at the same frequency. It was assumed that with higher PV penetration India will follow the UK and the two voltages mentioned would be the ones of significance.

Economic analysis is central to energy policymaking. Most economic analysis considered PV energy yield (in kWh) for a period of 1 year. As such, the efficacy of DSM and AVC for maximizing PV energy capture following the two-stage approach in Figure 8 is also assessed for a 1-year period for the scenarios considered. The Post-Curtailment Energy Yield Estimation (PC-EYE) algorithms for the three cases part of the assessment process namely (i) Base case (without DSM or AVC), (ii) Case with DSM, and (iii) Case with DSM and AVC, are shown below. MATLAB was used to code the algorithms. Bus voltages were calculated using Distflow (Distribution load flow).⁶⁷ The DSM and AVC programs were based on the schemes presented earlier in Figures 9 and 10. 1.14 p.u. was the threshold voltage at which curtailment action was initiated. The grid voltage upper limit of 1.1 p.u. was set as the voltage for initiating DSM and AVC actions to maximize energy capture by preventing curtailment.

The Post-curtailment energy yield estimation algorithms for the Base case, with DSM and with both DSM and AVC have been detailed below. PV energy curtailment is calculated in the following manner (un-curtailed energy yield is available from the PV generation profiles): Firstly, using the appropriate post-curtailment algorithm, record the instances where bus voltages are greater than 1.14 p.u. for certain hour of a day owing to PV generation. Record the PV generation corresponding to these hours and instances and the sum them to calculate the aggregate PV energy curtailment for the day. Then, the PV curtailment for every single day of a month recorded in this manner are aggregated at the end of a month to calculate the total PV curtailment for a certain month. After that, the values of PV curtailment in all 12 months are summed at the end of a meteorological year to get the total annual curtailment for that specific meteorological year. Same process is used to calculate PV curtailment at all buses investigated in the distribution network considered.

Algorithm 1. Post-curtailment energy yield estimation algorithm (Base case)

- 1: Read the PV penetration scenario.
 - 2: Read PV generation profile and net load profile for the day and location.
 - 3: In hourly time steps, run Distflow program $\{V_{n+1} = V_n - \left[\left(\frac{\sum_{k=1}^n P_k - jQ_k}{V_n} \right) \times Z_{(n+1)_n} \right]\}$ and record voltages at all Buses for all hours of the day.
 - 4: For all voltages greater than 1.14 p.u. from 3, turn all the PV systems at the relevant Buses off and record the value of PV energy curtailed at the bus. Aggregate the energy curtailed at each Bus over the day.
 - 5: Repeat 2–4 for all days of the year and aggregate the energy curtailed at each Bus over the year.
-

Algorithm 2. Post-curtailment energy yield estimation algorithm (DSM)

- 1: Read the PV penetration scenario.
- 2: Read PV generation profile and net load profile for the day and location.
- 3: In hourly time steps, run Distflow program $\{V_{n+1} = V_n - \left[\left(\frac{\sum_{k=1}^n P_k - jQ_k}{V_n} \right) \times Z_{(n+1)_n} \right]\}$ and record voltages at all Buses for all hours of the day.
- 4: For all Buses, check if voltage exceeds 1.1 p.u. at any step during the day. If yes activate the DSM program, run Distflow and record the newly resulted Bus voltages.
- 5: For all voltages greater than 1.14 p.u. from 4, turn all the PV systems at the relevant Buses off and record the value of PV energy curtailed at the bus. Aggregate the energy curtailed at each Bus over the day.
- 6: Repeat 2–5 for all days of the year and aggregate the energy curtailed at each Bus over the year.

Algorithm 3. Post-curtailment energy yield estimation algorithm (DSM and AVC)

- 1: Read the PV penetration scenario.
- 2: Read PV generation profile and net load profile for the day and location.
- 3: In hourly time steps, run Distflow program $\{V_{n+1} = V_n - \left[\left(\frac{\sum_{k=1}^n P_k - jQ_k}{V_n} \right) \times Z_{(n+1)_n} \right]\}$ and record voltages at all Buses for all hours of the day.
- 4: For all Buses, check if voltage exceeds 1.1 p.u. at any step during the day. If yes activate the DSM program, run Distflow and record the newly resulted Bus voltages.
- 5: For all Buses, check if voltage exceeds 1.1 p.u. at any step during the day. If yes activate the AVC program, run Distflow and record the newly resulted Bus voltages.
- 6: For all voltages greater than 1.14 p.u. from 4, turn all the PV systems at the relevant Buses off and record the value of PV energy curtailed at the bus. Aggregate the energy curtailed at each Bus over the day.
- 7: Repeat 2–6 for all days of the year and aggregate the energy curtailed at each Bus over the year.

4 | RESULTS AND DISCUSSION

Simulations were run for the 11 scenarios of varying PV penetration (steps of 10%) described in Section 2.2.1. Three different cases were considered: (i) Base case (without DSM or AVC), (ii) Case with DSM, and (iii) Case with DSM and AVC. Time period considered in the simulations was 1 year. It was identified that for both Newcastle and Mumbai, the mid-summer period is the period of highest irradiation in the year when voltage rise and consequently PV energy curtailment was most severe. The performance of the smart grid solutions considered for the worst-case scenario, the peak irradiation day in summer, is representative of the efficacy. Owing to this reason, some of the results discussed below only focus on the peak day in summer. The bus that is located the farthest from the main grid source (Bus 17) is the most severely affected by any reverse power flow from the domestic PV sources back to grid.⁶⁸ So, Bus 17 was chosen to visualize the effectiveness of DSM and AVC.

4.1 | Base case

4.1.1 | Newcastle case

Simulation results for the Newcastle case indicated that for the first 10 PV penetration scenarios, from 0% to 90% penetration level, there were no voltage limit (1.1 p.u.) violations at any Buses. Figure 14 shows the Bus voltages at 90% penetration for the peak summer day. For the 100% PV penetration scenario, voltage limit violation was found to occur for Bus 13 to Bus 17. Figure 15 shows Bus 17 voltage and duration of PV energy curtailment for this scenario. The curtailment voltage threshold of 1.14 p.u. was never exceeded even for the 100% PV penetration scenario. Evidently, revision of the grid code from G83 to G98 and changing the disconnection threshold has had a positive impact on PV energy capture. Under G83's curtailment voltage threshold of 1.1 p.u., the aggregate annual energy curtailment between Bus 1 and Bus 17 would have been 15,911 kWh.

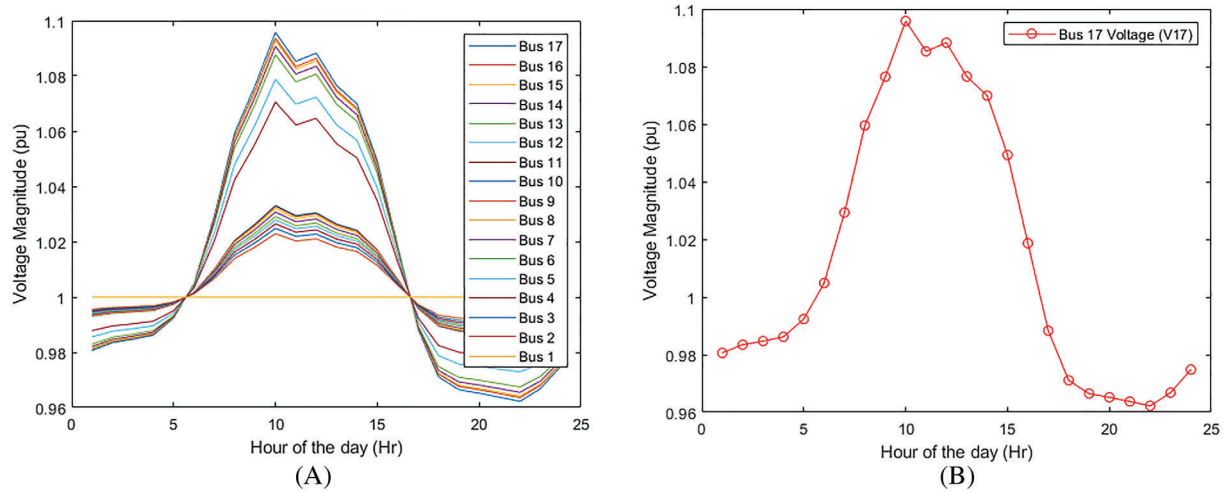


FIGURE 14 (A) Bus voltages and (B) Bus17 voltage at 90% PV Penetration for the Newcastle case during the peak summer day

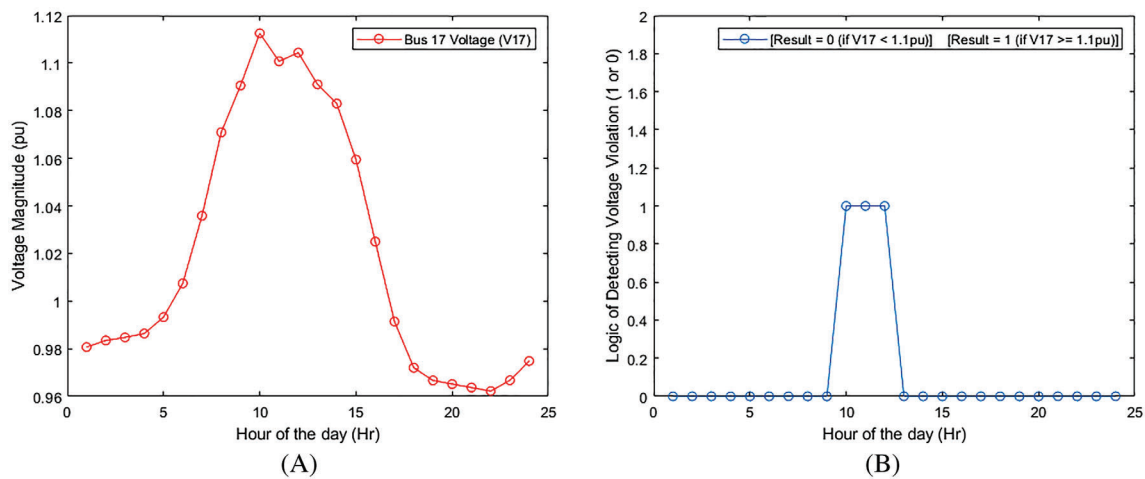


FIGURE 15 (A) Bus 17 voltage and (B) duration voltage limit violation at 100% PV penetration for the Newcastle case during the peak summer day

4.1.2 | Mumbai case

Simulation results for the Mumbai case indicated that for up to 40% PV penetration level there were no voltage limit violations at any Buses. Figure 16 shows the Bus voltages at 40% penetration for the peak summer day. Table 2 lists the higher PV penetration scenarios and the Buses which were affected by voltage limit (1.1 p.u.) violations respectively for each scenario. Figure 17 shows the voltages at all Buses for PV penetration levels from 50% to 100%. Figures 18 and 19 show Bus 17 voltage and duration voltage violation for the 50% and 100% PV penetration. The severity of voltage rise with increasing PV penetration is clearly evident. The threshold voltage of 1.14 p.u. was exceeded for scenarios with PV penetration level from 70% and above. Figure 20 provides a summary of curtailment results.

For the typical meteorological year, the simulation results showed that Buses 15–17 were affected by PV energy curtailment when the PV penetration level exceeded 70%. Buses 14–17 were affected by PV energy curtailment when the PV penetration level exceeded 80%. And, Buses 13–17 were affected by PV energy curtailment when the PV penetration level reached 100%. At 100% PV penetration the annual energy curtailment at Bus 17 is 48,941 kWh which meant that 81% of the annual energy generation from the residential PV systems connected to the Bus will be curtailed. At 70% penetration, the respective curtailment value was 29% of the annual energy generation at the Bus. For PV systems connected to Bus 15, the curtailment was a mere 1% of the annual energy produced by the systems at 70% penetration. However, at 100% penetration, the curtailment was 72% of the annual energy produced by the PV systems connected to the Bus. For Bus 13,

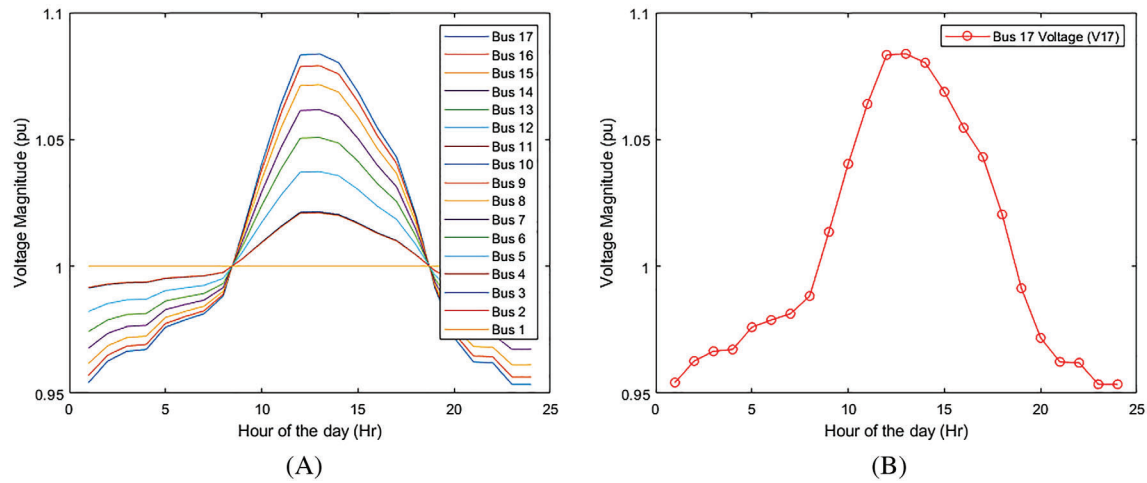


FIGURE 16 (A) Bus voltages and (B) Bus 17 voltage at 40% PV Penetration for the Mumbai case during the peak summer day

TABLE 2 PV penetration level versus Buses with voltage limit violation for the Mumbai case during the peak summer day

PV penetration level (%)	Buses with voltage violation (>1.1 p.u.)
50%	Bus 17
60%	Bus 15, Bus 16, Bus 17
70%	Bus 14, Bus 15, Bus 16, Bus 17
80%	Bus 13, Bus 14, Bus 15, Bus 16, Bus 17
90%	Bus 13, Bus 14, Bus 15, Bus 16, Bus 17
100%	Bus 12, Bus 13, Bus 14, Bus 15, Bus 16, Bus 17

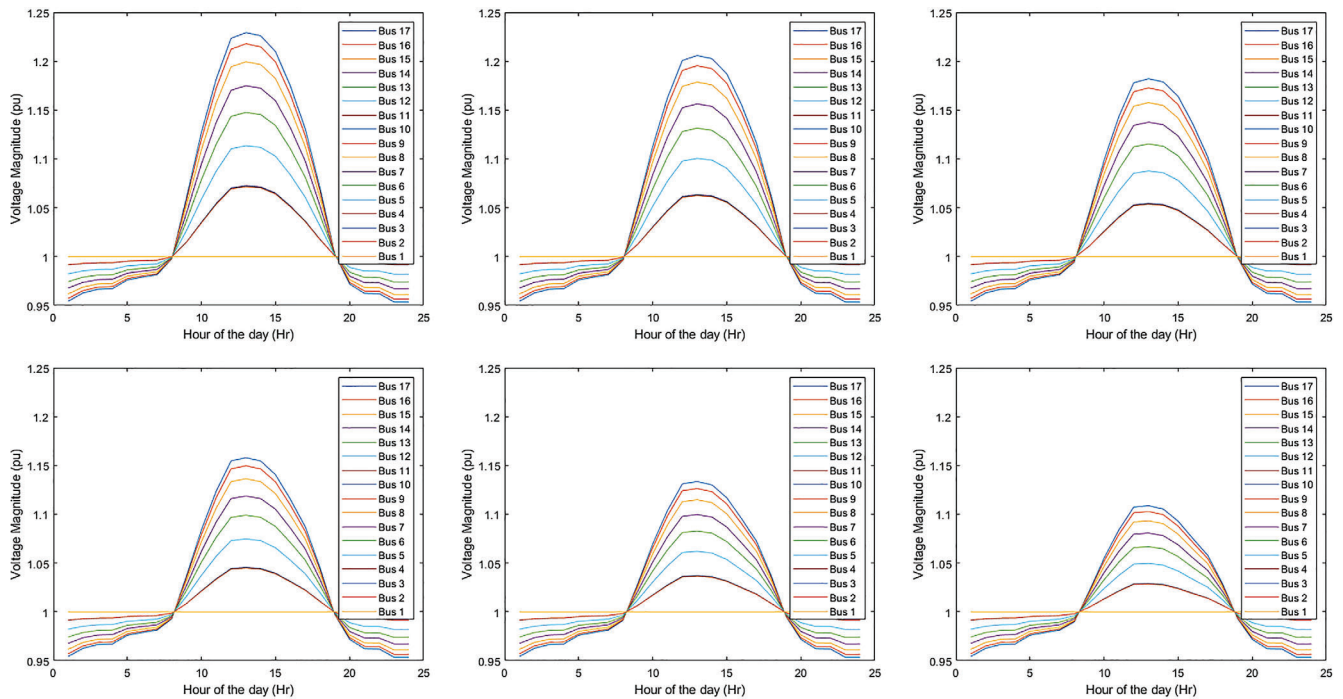


FIGURE 17 All Bus voltage for 50%–100% PV penetration levels for the Mumbai case during the peak summer day

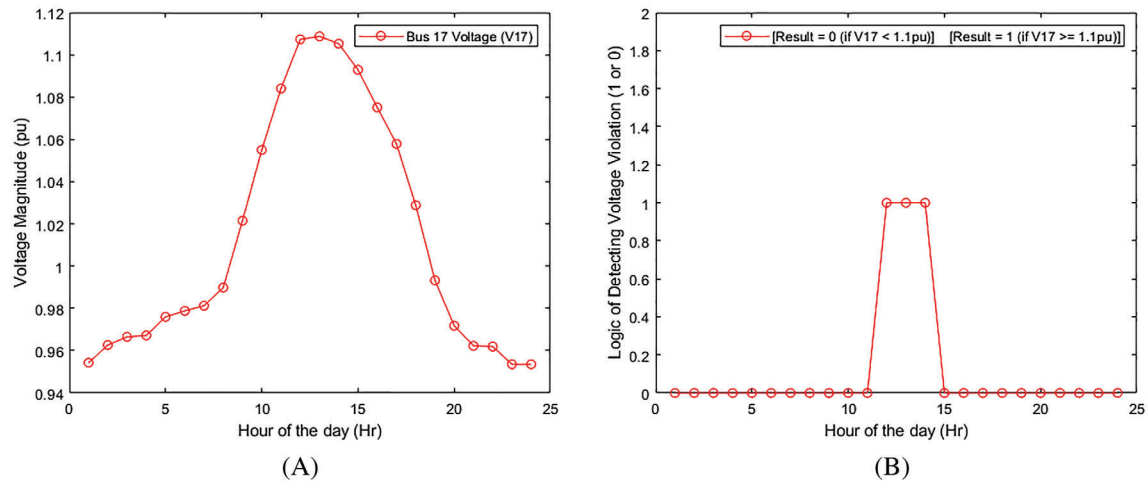


FIGURE 18 (A) Bus 17 voltage and (B) duration of Bus 17 voltage limit violation at 50% PV penetration for the Mumbai case during the peak summer day

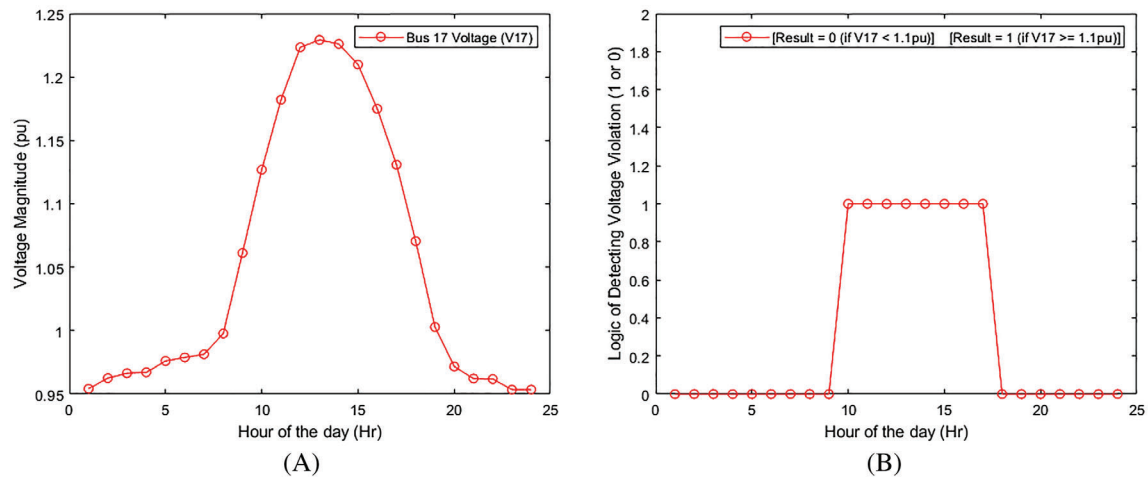


FIGURE 19 (A) Bus 17 voltage and (B) duration of Bus 17 voltage limit violation at 100% PV penetration for the Mumbai case during the peak summer day

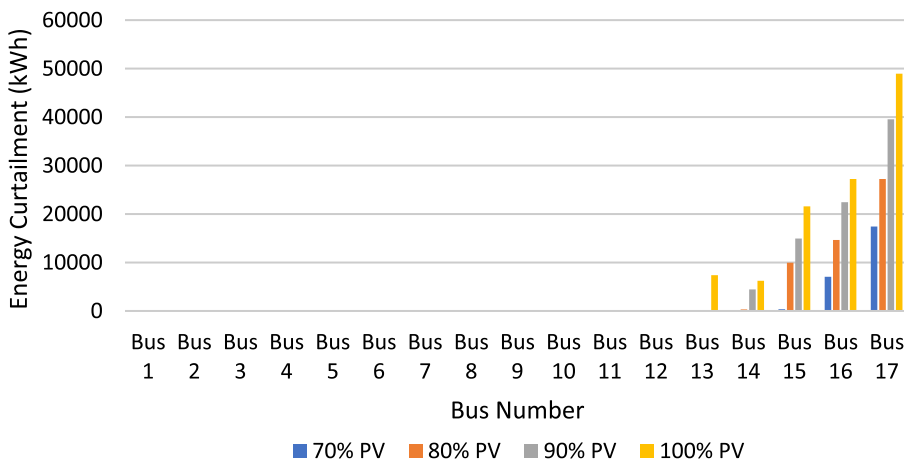


FIGURE 20 Annual energy curtailment for the base case in Mumbai

curtailment only happened for the 100% scenario. The aggregate energy curtailment at the Bus of 7381 kWh translated to approximately 24% of the annual energy yield of PV systems connected to the Bus being curtailed.

4.2 | Case with DSM

4.2.1 | Newcastle case

Two DSM participation scenarios were considered. A high customer participation scenario considered 50% of the houses in the network participating in DSM. A lower customer participation scenario considered 15% of the houses in the network participating in DSM and is assumed to be a more accurate representation of current customer behavior. PC-EYE (with DSM) algorithm was run with DSM program following the scheme in Figure 9 (Section 3) for the flexible load categories Washing machine, Dishwasher, and Electric water heating as described in Section 2.3.1.

It can be seen from Figure 21 that the voltage violation at the most sensitive Bus (Bus 17) was fully compensated by the DSM program when 50% of the houses in the network participated in DSM. However, 15% of houses participating in DSM was not able to fully compensate the voltage limit violation as can be seen from Figure 22. The duration of voltage violation, however, was shortened. Voltage violation at 11 AM was eliminated but those at 10 AM and 12 noon remained.

4.2.2 | Mumbai case

A high and a low DSM participation scenario were considered as in the case of Newcastle with 50% and 15% housing participation, respectively. Results showed that DSM had minimal impact for the Mumbai case. Figure 23 compares Bus 17 voltage with 50% DSM participation to the Base case for 70% PV penetration, which was the minimum penetration level to have energy curtailment in the Base case. There is no impact on voltage violation and PV energy curtailment was not compensated. Figures 24 and 25 show the aggregate annual energy curtailment for all Buses with 15% and 50% DSM participation. There is very little improvement from the Base case curtailment shown previously in Figure 20. Despite being the comparatively easier to realize solution for India, DSM did not prove to be an effective solution for maximizing PV energy capture. This is due to the high solar resource of India. While the residential distribution network in Newcastle is based on copper cables, the system in Mumbai utilizes aluminum overhead conductors. This difference in network topology, also means that Mumbai is more susceptible to voltage limit violations under high PV penetration.

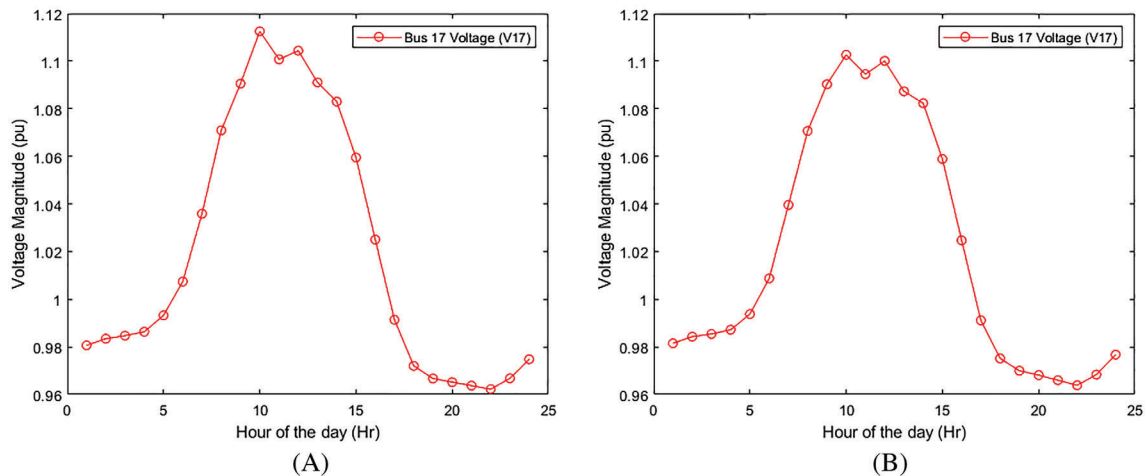


FIGURE 21 Bus 17 voltages for the Newcastle case at 100% PV penetration during summer (A) Base case and (B) with 50% housing participation in DSM program

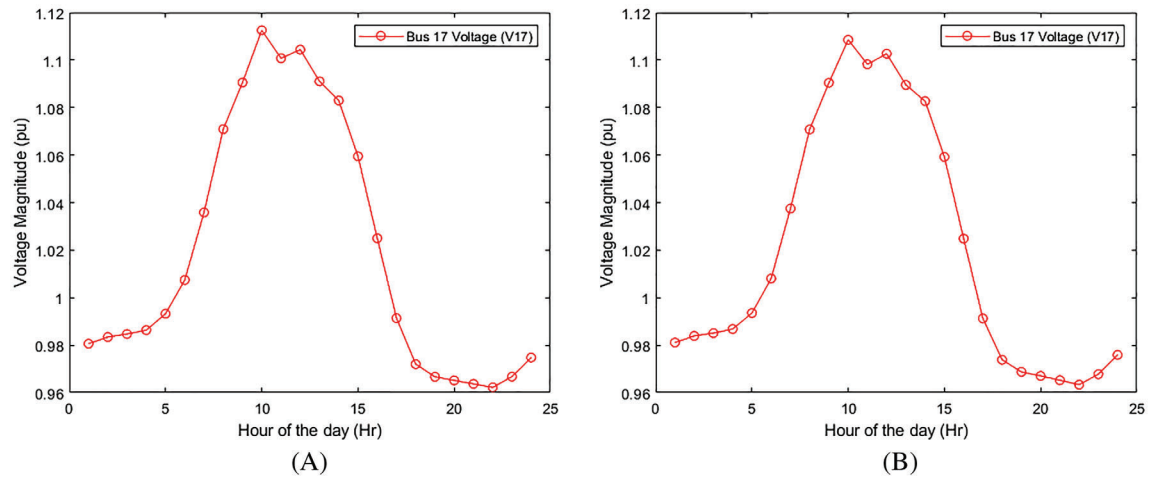


FIGURE 22 Bus 17 voltages for the Newcastle case at 100% PV penetration during summer (A) Base case and (B) with 15% housing participation in DSM program

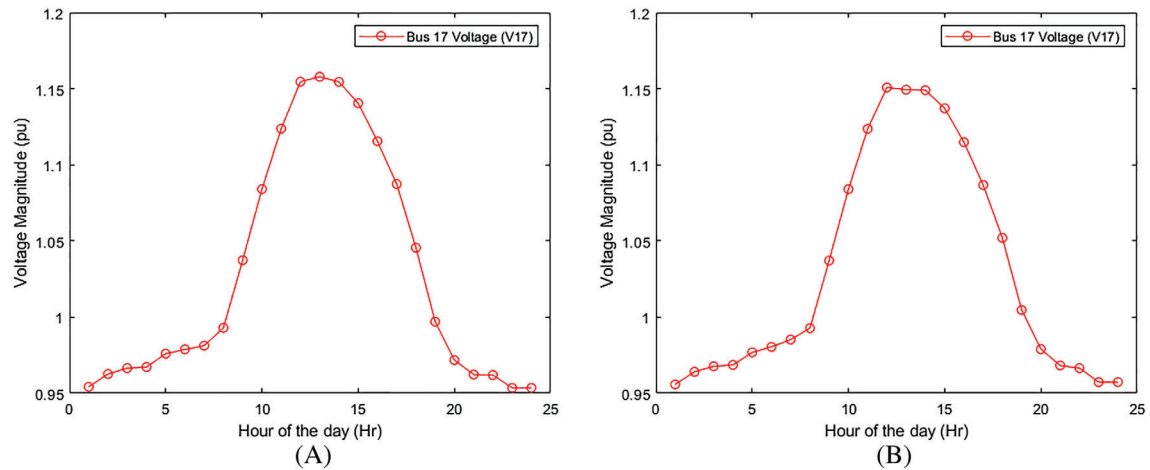


FIGURE 23 Bus 17 Voltages for the Mumbai case at 70% PV Penetration during summer (A) Base case and (B) With 50% of housing participation in DSM program

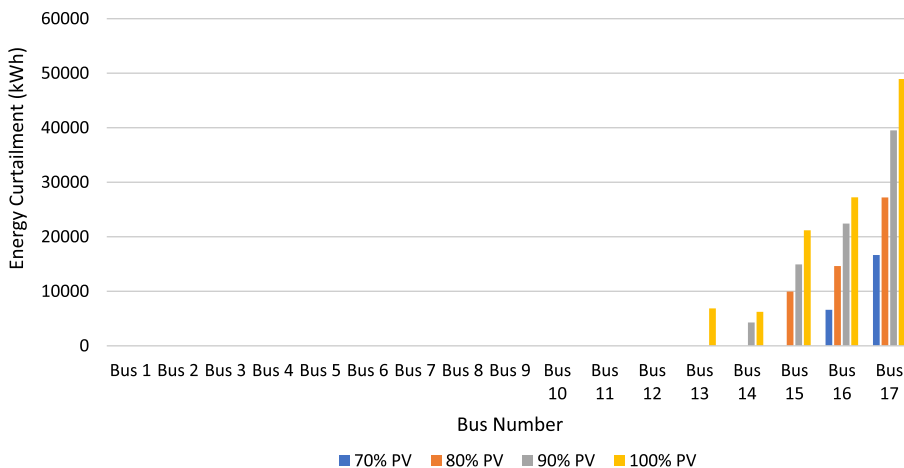


FIGURE 24 Annual energy curtailment for the Mumbai case with 15% housing participation in DSM

FIGURE 25 Annual energy curtailment for the Mumbai case with 50% housing participation in DSM

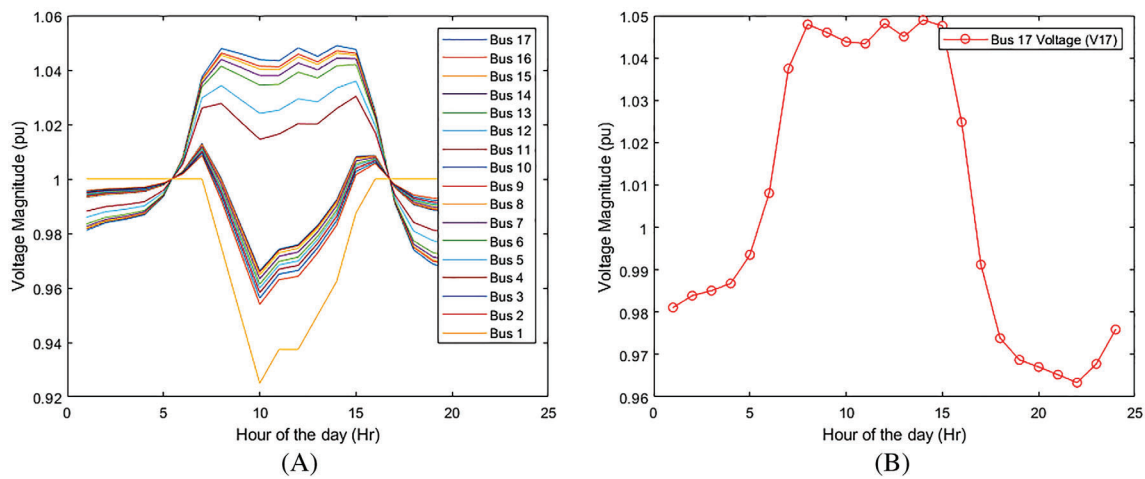
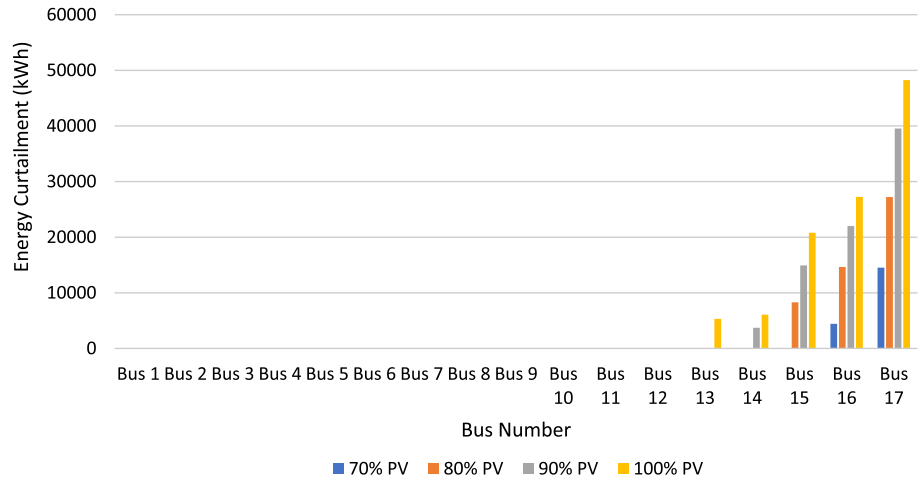


FIGURE 26 (A) Bus voltages and (B) Bus 17 voltage at 100% PV penetration for the Newcastle case during peak summer with 15% housing participation in DSM and AVC

4.3 | Case with DSM and AVC

4.3.1 | Newcastle case

Results from running the PC-EYE algorithm with DSM and AVC with 15% housing participation in DSM not only shortened the duration of voltage violation, but also fully compensated it. Figure 26 shows all Bus voltages. Bus 17, where there was voltage limit violation even with DSM, showed no violation when AVC was combined with DSM. The combination of AVC and DSM is found to be efficient in fully eliminating voltage violations for the Newcastle network for the worst-case high PV penetration scenario.

4.3.2 | Mumbai case

Results from running the PC-EYE algorithm with DSM and AVC with 15% housing participation in DSM for 70%–100% PV penetration is shown in Figures 27–31. The OLTC tap change action by the AVC program and its impact on voltage profiles is evident from the figures. It was identified from earlier simulations that DSM had minimal impact on clearing voltage violation and reducing PV curtailment for Mumbai. Figures 27 and 28 show that up to 80% PV penetration can be accommodated in the Mumbai case study network without voltage limit violation or PV energy curtailment, by combining AVC with DSM.

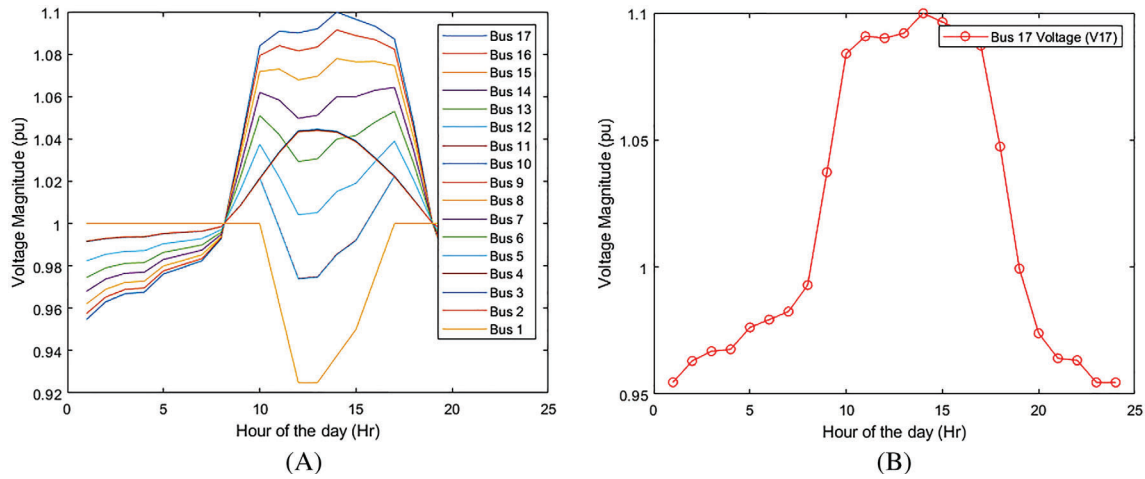


FIGURE 27 (A) Bus voltages and (B) Bus 17 voltage at 70% PV penetration for the Mumbai case during peak summer with 15% housing participation DSM and AVC

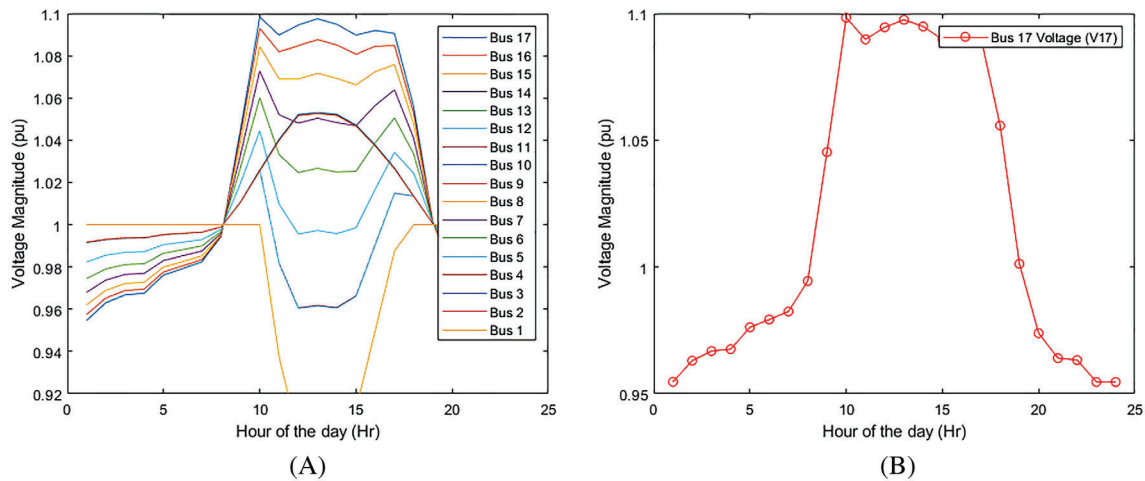


FIGURE 28 (A) Bus voltages and (B) Bus 17 voltage at 80% PV penetration for the Mumbai case during peak summer with 15% housing participation DSM and AVC

It can be seen from Figure 29 that when the PV penetration is 90% in Mumbai network voltage violation still existed at Bus 16 and 17 for which voltages were greater than 1.1 p.u. However, the duration of voltage violation was shortened. All Bus voltages were less than curtailment threshold voltage of 1.14 p.u. Consequently, combining DSM with AVC was able to eliminate PV energy curtailment in the network completely even at 90% penetration. This can only be the impact of AVC, as it was evident from simulations in the previous section that DSM alone had minimal impact for the Mumbai case.

In contrast to the results at 90% PV penetration, voltage limit violation and PV energy curtailment remained when PV penetration was at 100%. As seen in Figure 30, Buses 15–17 were affected by voltage limit violation even with AVC and DSM. Only Bus 16 and 17 voltages were above the curtailment threshold. It can be seen from Figure 31 that the duration of voltage limit violation was considerably reduced when AVC was applied with DSM. Impact of OLTC hitting tap limits during AVC is evident from voltages of Buses close to OLTC in Figure 30.

As shown in Figure 32, there is a significant reduction in the amount of PV energy curtailed in a year when AVC was applied in combination with DSM. DSM in this case was with 15% housing participation. The curtailment that still existed at 100% PV penetration with 15% DSM and AVC was only at Buses 16 and 17. Annual energy curtailed was 1208.4 kWh at Bus 16 while it was 13,706.8 kWh at Bus 17. For a typical PV system connected to Bus 17, curtailment was around 23% of its annual energy yield, whereas the value was at 80% for the Base case without DSM and AVC. The base case (refer to Figure 20) also had curtailment from Bus 13 onwards. At 100% PV penetration, the aggregate annual energy

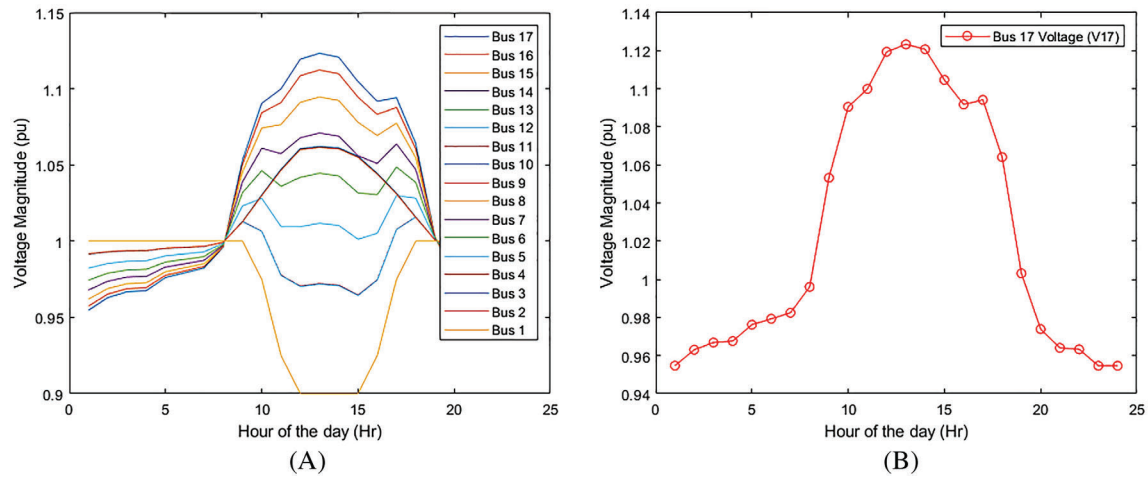


FIGURE 29 (A) Bus voltages and (B) Bus 17 voltage at 90% PV penetration for the Mumbai case during peak summer with 15% housing participation DSM and AVC

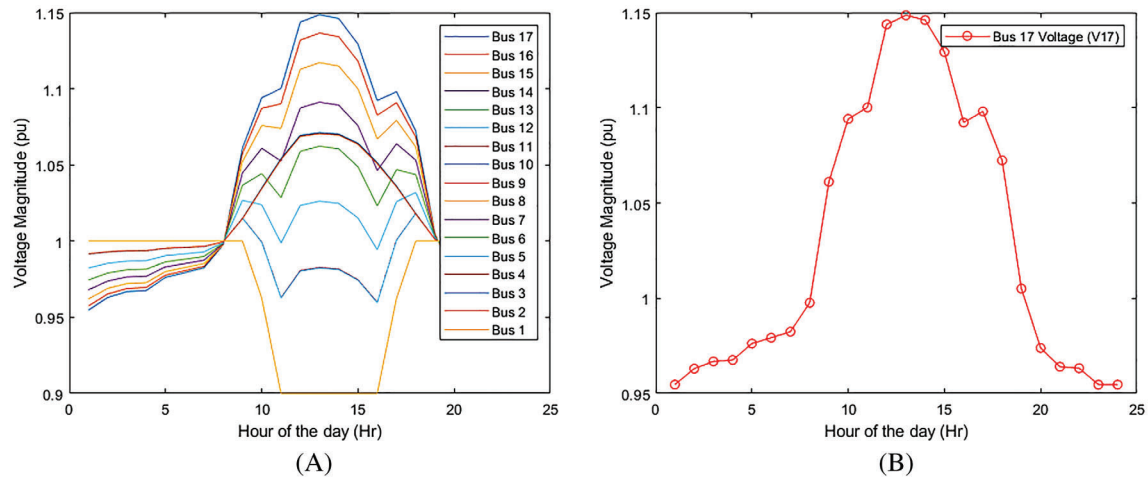


FIGURE 30 (A) Bus voltages and (B) Bus 17 voltage at 100% PV penetration for the Mumbai case during peak summer with 15% housing participation DSM and AVC

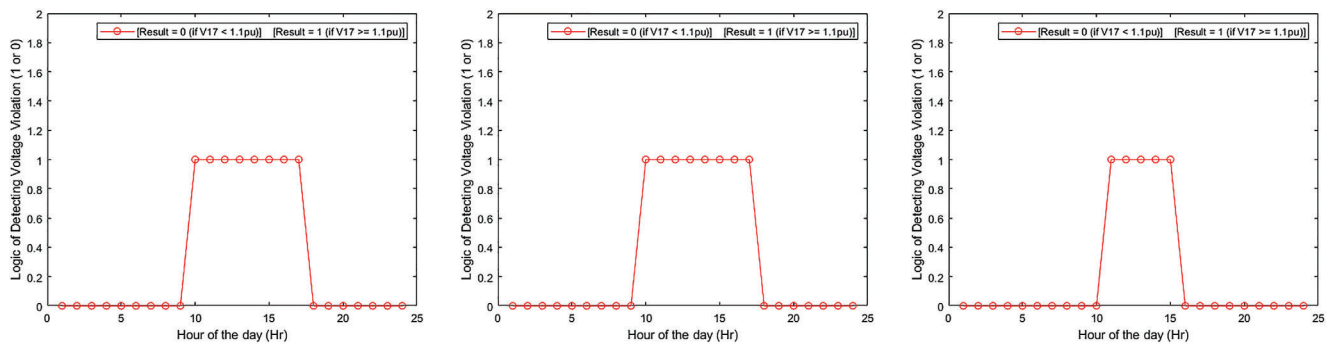


FIGURE 31 Duration of Bus17 voltage violation for the Mumbai case at 100% PV penetration during peak summer (A) Base case, (B) 15% housing participation DSM and (C) 15% housing participation DSM + AVC

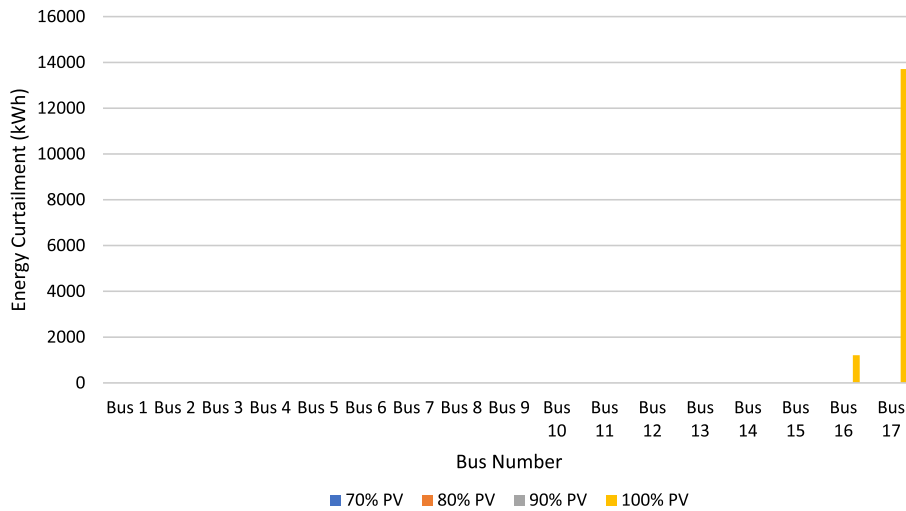


FIGURE 32 Annual energy curtailment for the Mumbai case with 15% housing participation DSM and AVC

TABLE 3 Summary of aggregate annual PV energy curtailment in the LV network for the Mumbai case

Scenario	Total PV energy curtailment in Base case (kWh)	Total PV energy curtailment with 15% DSM (kWh)	Total PV energy curtailment with 50% DSM (kWh)	Total PV energy curtailment with 15% DSM + AVC (kWh)
70% PV Penetration	24,802.9	23,270.3	18,945.6	0
80% PV Penetration	52,129.6	51,808.9	50,161.2	0
90% PV Penetration	81,338	81,159.7	80,179.7	0
100% PV Penetration	111,380.2	110,470.6	107,690.5	14,915.2

curtailment in the LV network with 15%DSM and AVC was 110,470.6 kWh. When the higher participation scenario, with 50% houses participating in DSM was considered along with AVC, the reduction in aggregate annual energy curtailed in the LV network from PV systems at 100% penetration was a mere 2.5%. This is indicative of AVC being more effective than DSM for the Indian network and solar resource conditions. Table 3 summarizes the aggregate annual PV energy curtailment in the LV network for the Mumbai case for all scenarios where curtailment occurred.

It is clear that the houses connected to buses which are far away from the main grid source may not harvest as much energy from their own PV systems because of the shut-down time of their PV inverters when the voltage exceeds a certain limit of 1.14 p.u. DSM and AVC aids maximization of energy capture because of the reduction in curtailment. The average amount of financial loss prevented because of the reduction in curtailment can be calculated as⁶⁹:

$$\text{Prevented Financial Loss (per year)} = \text{Amount of curtailment reduced} \times \text{Electricity Unit Price} \quad (5)$$

The reduction in curtailed energy means more power is consumed from the PV system rather than from the grid source. Prevented financial loss is therefore because of the reduction in grid import. Cost of a kWh of electricity in India on average is INR 6.034.⁷⁰ Table 4 summarizes the prevented financial loss at different PV penetration levels for the Mumbai case when 15% DSM is used in combination with AVC.

Given the economic situation and consumer purchase power index in India, the financial savings to customers with DSM and AVC is significant. As voltage limit violations and reverse power flow are reduced and consequently the negative impact on network assets are limited, networks would be able to manage operations with the aging assets. Increasingly, electricity utilities are penalized for carbon emission and are given long term carbon emission reduction targets. Hence, there is also significant potential for avoided costs from the side of utility if renewable generation such as PV are maximized by means of these smart grid solutions. However, the actual value of avoided costs will depend on the nation's energy policies.

TABLE 4 Prevented financial loss at different PV penetration levels for the Mumbai case

Bus No.	Prevented financial loss per year in INR at 70% PV penetration	Prevented financial loss per year in INR at 80% PV penetration	Prevented financial loss per year in INR at 90% PV penetration	Prevented financial loss per year in INR at 100% PV penetration
Bus 13	-	-	-	8907.13
Bus 14	-	968.99	13,426.28	18,838.27
Bus 15	427.37	12,004.53	18,017.37	26,044.37
Bus 16	7083.39	14,725.33	22,557.68	26,171.31
Bus 17	10,502.38	16,426.36	23,852.50	21,258.64

5 | CONCLUSIONS

Future power networks are certain to have high penetration levels of renewable generation in the distribution network. With high penetration levels of microgeneration, curtailment of PV output according to grid code mandates during peak generation and low demand period is anticipated. For example, according to Engineering Recommendation G98, PV systems in the UK LV distribution networks are required to curtail generation when the voltage rise at the point of connection exceeds the mandated limit. Power networks are currently moving into the smart grids paradigm. The inherent cost attached to smart grids technologies means that the global economic inequality will be reflected in their deployment. Developing nations with lower economic reserves to spare are often constrained in terms of the level and nature of changes they could make to their power networks.

It was evident from literature that while there is a strong focus within research studies on impacting sustainable energy policies for developing nations, the focus is mostly at the higher-level vision-type policies at the national level, rather than policies or grid codes at the operational level especially at the LV level. This work increments the state-of-the-art by supporting power system planning by means of scenario-based impact assessments and thus aiding sustainable energy policymaking for developing countries. Based on use case scenarios, the efficacy of smart grid solutions DSM and AVC in maximizing PV energy yield and therefore revenue returns for prosumers and avoided costs for distribution networks between a developed country (the UK) and developing country (India) is analyzed.

The results showed that while DSM could be a preferred means because of its potential for holistic deployment (PDSM) via demand response scheme for India and similar developing nations, technically the combination of the weaker LV network with significantly higher solar resource meant that it is not effective in preventing PV energy curtailment. Developing nations like the UK have upgraded their policies and grid codes to facilitate higher energy capture from renewable like PV. The positive impact of the move from grid code G83 to G98 and modification of voltage-based curtailment threshold was observed in the PV energy yield captured. For the Newcastle case study, the results obtained show that there is no PV energy curtailment at all even in the base case scenario under G98. For the Mumbai case, under the studied conditions, combining AVC extended the PV penetration level without curtailment from 70% to 90%, if the grid code was equivalent to G98.

While the Indian government has set ambitious targets for renewable installed capacity as well as higher-level 5-year plans for achieving them, grid codes equivalent to G98 in the UK are still in development. Results of this work demonstrated that, while smart grid solutions are capable of enabling PV generation maximization and improving penetration levels, the extent of such benefits are location-specific and are affected by the distribution network structure. It is recommended that, in preparation of grid codes, scenario-based assessments are carried for other renewable energy maximization methods as well with a focus on load profiles as well as the locational renewable resource conditions as demonstrated in this work. Future work will explore the methods to compensate the energy loss and power quality problems in potential scenarios of increasing housing demand and PV penetration coming into existing distribution networks as well as the potential of local autonomous inverter control at the PV sites.

ACKNOWLEDGMENTS

This research was partially funded as a PhD studentship under the ‘Stability and Performance of Photovoltaics (STAPP)’ project funded by Research Councils UK Energy Programme in UK (contract no: EP/H040331/1). The first author gratefully acknowledges his PhD supervisors Prof Ghanim Putrus and Prof Nicola Pearsall for their technical support during initial stages of the work. The second author acknowledges the Graduate Tutorship from Teesside University which funded his research contribution to the work. The authors also thank Vandana Singal, Central Electricity Authority of India for the Indian distribution network model.

PEER REVIEW INFORMATION

Engineering Reports thanks the anonymous reviewers for their contribution to the peer review of this work.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

AUTHOR CONTRIBUTIONS

Gobind Pillai: Conceptualization; resources; supervision; writing-original draft; writing-review & editing. **Michael Allison:** Investigation; methodology; validation; writing-review & editing. **Thet Paing Tun:** Investigation; methodology; validation; writing-review & editing. **Kiran Chandrakumar Jyothi:** Formal analysis; writing-original draft. **Eaby Kollonoor Babu:** Software; writing-original draft.

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How to cite this article: Pillai G, Allison M, Tun TP, Chandrakumar Jyothi K, Kollonoor Babu E. Facilitating higher photovoltaic penetration in residential distribution networks using demand side management and active voltage control. *Engineering Reports*. 2021;e12410. <https://doi.org/10.1002/eng2.12410>